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### MICRO-FINANCE ANALYTICS AND CHALLENGES OF FINANCIAL INCLUSION AMONG UNDERSERVED POPULATION IN OYO STATE OF NIGERIA

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#### **Abstract**

*Despite various global efforts to close the financial gap, millions of individuals and small business in rural communities remain excluded from formal financial system due to limited access, financial illiteracy and systemic inefficiencies. The study investigates the role of microfinance analytics in solving challenges of financial inclusion among underserved populations in Iseyin area of oyo state, Nigeria. The research employed survey research method. A population of one thousand (1,000) individuals from underserved rural community of Iseyin in Oyo state of Nigeria. A stratified random sampling of microfinancing clients was used to select three hundred (300) participants comprising of existing and potential clients as well as stakeholders. Data was collected through structured questionnaire. Analytical tools such as descriptive statistic and ordinary least square method were used to analyse the data. Findings revealed that Microfinance analytics significantly enhance financial inclusion by improving risk assessment, adapting financial products to clients needs and help optimize resources allocation. The study concludes that micro-finance analytics is a transformative tool for addressing financial exclusion. To maximise its impact, the study recommended the Integration of lightweight's micro-finance analytics into MFIs loan processing workflow and make it the default decision support tool. These would include piloting a cloud based analytic engine, using the dashboard during clients' interview and setting clear Key performance index (KPI). The expected outcome of the implementation is that it would increase financial inclusion and high portfolio quality is maintained.*

*Keywords: Analytics; Data-driven innovation; Micro-finance institutions (MFI's), Underserved populations.*

*JEL: G21, O33, C55, I38*

#### **INTRODUCTION**

Microfinance has long been hailed as a catalyst for financial inclusion in Nigeria, yet the sector still grapples with deep rooted barriers that keep large segments of the population underserved. Recent scholarship highlights how data driven analytics can bridge this gap. Nwaimo,

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Adegbola & Adegbola (2024) introduced a machine learning credit-scoring framework that boosted loan approval rates by up to 30 % in pilot trials, showing the power of predictive models to identify viable borrowers who lack traditional credit histories . Complementing this, Okafor (2025) demonstrated that ensemble techniques especially Gradient Boosting can predict defaults with an AUC of 0.94, underscoring the value of advanced analytics in risk management for Nigerian microfinance institutions (MFIs).

Notwithstanding the enormous potential offered, microfinance still confronts several obstacles, from problems with operational effectiveness to problems with the objective of inclusive economic growth. The field of microfinance analytics is expanding and uses data-driven techniques to evaluate the impact, sustainability, and efficacy of MFI interventions. This involves, among other things, determining the clients' financial stability, their ability to repay loans, and the social results of the microcredit program. Microfinance institutions can enhance their service offerings, more effectively target the population that needs them most, and optimize their operations to expand their reach and influence at the right time and place by utilizing data analytics. Numerous obstacles still stand in the way of accomplishing the aforementioned goals, such as restricted access to financial services in isolated areas, expensive service delivery costs, low-income levels of the targeted clientele, excessive debt, and repayment patterns of consumers. Additionally, a rigorous examination of the sociocultural elements affecting underprivileged groups' financial decision-making was required.

Adebayo O. Adeyemi (2025) notes in a study in Oyo State that without adequate digital literacy, the analytical capabilities of MFIs cannot be fully leveraged to reach underserved population. In Oyo State, financial inclusion picture is a mix of stark contrasts and recent progress. The latest data show that while 78 % of urban residents have active mobile money accounts, only about 23 % of rural women do, leaving roughly 61 % of them in multidimensional poverty. In real terms, women without a mobile wallet experience poverty intensity 3.8 times higher and save 42 % less than their digitally included peers .

This paper examines the intersection of microfinance analytics and the challenges faced to achieve financial inclusion. It is crucial to critically examine the wider implications for economic development and poverty reduction among underserved populations, particularly in developing countries, and to consider how data-driven insight can help provide solutions to these challenges. In order to overcome these challenges, innovative microfinance service models and the adoption of new technologies, such as mobile banking and digital platforms, are to be integrated in order to reduce operational costs and enhance wider access.

### **Statement of the Problem**

A sizable portion of the underprivileged population is still not included in the formal financial system, despite tremendous global advances in improving financial inclusion. By providing small-scale financial services to low-income individuals and enterprises, microfinance institutions, or MFIs, have become a vital force in closing this gap. However, these institutions' scalability and efficacy are hampered by problems like a lack of data-driven decision-making, operational inefficiencies, poor risk assessment, and regulatory concerns.

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According to Adebayo O. Adeyemi (2025), lack of data-driven decision-making, operational inefficiencies, poor risk assessment, and regulatory concerns are made worse by a lack of strong microfinance analytics, which makes it difficult for many MFIs to precisely determine the needs of their clients, assess their creditworthiness, and put sustainable financial plans into place. Additionally, Tajudeen A.O. (2015) and Peter K.O. (2022) noted that underprivileged groups frequently encounter obstacles including high transaction fees, restricted access to technology, and financial illiteracy, which hinders their capacity to take use of the microfinance services that are offered to them. Therefore, the goal of the study is to investigate how microfinance analytics can help address the issues of financial inclusion by examining how data-driven insight and sophisticated analytical tools can improve outreach, increase operational efficiency, and promote financial empowerment among underserved populations in Iseyin area of Oyo state. The goal of the project is to help create a financial ecosystem that is more inclusive.

Examining how microfinance analytics and the difficulties of financial inclusion among marginalized groups are related reveals that most research is conducted in urban areas where traditional banking services are already available, highlighting the true goal of offering financial services to those who are not banked. By providing a thorough analysis of the actual unbanked or underserved population in rural areas, this study seeks to close this gap by identifying the main obstacles to financial inclusion and demonstrating how microfinance institutions can bridge the gap through digital infrastructure. In order to promote beneficial socioeconomic changes through financial inclusion among marginalized people in Nigeria's microfinance landscape, the research hopes to significantly add to the conversation surrounding digital innovation in microfinance.

## LITERATURE REVIEW

### Conceptual clarification

Small-scale financial services including loans, savings, and insurance that are offered to those without access to traditional banking services especially low-income individuals and small businesses are referred to as microfinance, according to Robinson (2001). According to Ledgerwood (1999), microfinance is the provision of financial services to low-income customers, particularly independent contractors, with the goal of giving them access to credit and other financial goods that are unavailable to people who are not part of the official banking system. Microfinance, according to Yinnus (1998), is a program that gives small loans to the impoverished, particularly women, so they can launch or grow their small, revenue-generating enterprises.

Micro-finance analytics, according to Gutierrez-Nieto et al. (2021), is the use of business analytics to assess and improve financial performance and social impact within microfinance institutions that use technology to increase their effectiveness and efficiency in serving the low-income population. According to Kudyba (2016), microfinance analytics are data-driven incentives that use analytics and data to improve the services that microfinance institutions offer. Microfinance analytics, according to Kumar et al. (2020), is the analytical study of microfinance services with an emphasis on origin, services, and limits. Through in-depth research in marginalized communities, it focuses on the evolution and difficulties of microfinance. Financial performance measures, analytics of consumer behavior, and impact evaluation tools are among the essential elements.

The practice of guaranteeing underprivileged populations have access to timely, reasonably priced, and sufficient financial products and services is known as financial inclusion. Access to credit, savings, insurance, and payment systems are the main markers. Challenges to financial inclusion as offered by Kumar et al (2020) refers to the obstacles that the underprivileged community must overcome in order to obtain financial services and products. Low financial literacy, restricted access to technology, operational difficulties for MFIs, risk assessment for unbanked clients, and inadequate data technology infrastructure are some of these issues.

### **Theoretical Framework**

The theory of financial intermediation was formalized by Gurley and Shaw (1960), which underpins microfinance, describes how financial institutions address the issues of transaction costs and knowledge asymmetry while extending credit. It draws attention to important elements including moral hazard, adverse selection, and the function of social capital. The hypothesis describes how MFIs serve as go-betweens for savers and borrowers. Additionally, MFIs use the social capital theory to leverage social capital through group lending structures, which lower default risks through peer monitoring and trust. According to the theory, relationships and social networks are essential to guaranteeing credit payment. When it comes to making financial decisions, underprivileged groups typically encounter emotional and cognitive obstacles. Therefore, microfinance products are designed to simplify their financial decisions to incorporate behavioral nudges that encourage savings and be payments discipline.

According to the empowerment idea, entrepreneurs can raise their standard of living by having access to financing. Microfinance empowers people, especially small businesses and those with modest incomes. MFIs have the ability to promote economic empowerment and financial inclusion for vulnerable groups, but they also face inherent obstacles that call for creative solutions. These include utilizing technology, enhancing financial literacy, creating culturally sensitive products, and strengthening regulatory frameworks that are necessary for long-term effects.

### **Empirical Reviews**

Providing financial services to people and small enterprises without access to traditional banking systems is known as microfinance. Its main objective is to encourage financial inclusion and reduce poverty by encouraging marginalized groups to participate in the economy. A thorough analysis of 1,552 articles published between 1987 and 2022, for example, offers valuable insights about the development of microfinance research. Microfinance and Financial Inclusion, a 2023 study, explores how microfinance aids in financial inclusion and the fight against poverty in India. Morduch (2023). Shreya Biswas (2021) investigates the connection between personal financial behavior and mobile financial services. Results show that these services raise the probability of borrowing from official financial institutions, investing, and obtaining insurance. Luke Lee (2024) investigates how alternative lenders and digital banks affect financial inclusion. The study highlights how digital platforms and approaches might improve marginalized communities' financial accessibility.

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Additionally, Weeks and Christiansen (2020) examine financial inclusion among the impoverished by presenting an examination of the diverse effects of expanded access to microcredit using data from three randomized trials. The study came to the conclusion that financial inclusion and data-driven microcredit provision are positively correlated. In a paper reviewing the role of microfinance in social development, Kabeer (2021) stated that it is an important tool for development strategy, offering financial services to economically productive but disadvantaged members of society. According to Klapper and Singer (2022), data analytics can be used to better analyze and identify unbanked people, boost financial literacy, improve credit scoring and risk assessment using alternative data sources, and create personalized financial solutions.

### METHODOLOGY

A Survey research approach is used in this study that embrace quantitative research techniques. This technique improves the depth of research findings by allowing for analysis of numerical data. A population of one thousand (1,000) individuals from underserved rural community of Iseyin in Oyo state of Nigeria was emerges for the study. A stratified random sampling of micro-financing clients was used to select three hundred (300) participants comprising of existing and potential clients as well as stakeholders. Data was collected through structured questionnaire. The tool is intended to record important variables pertaining to financial inclusion issues and microfinance analytics. A pre-test was conducted on the research instrument, using thirty (30), micro-financing clients outside the study area. The cronbach’s alpha statistic was computed with the aid of the Statistical Package for Social Science (SPSS) version 23, to ascertain the reliability of the developed instrument. The result shows that all the variables have reliability greater than 0.70, which is the minimum acceptable threshold, according to (Nunnally, 1978). Mugenda & Mugenda, (1999) rule of thumb also gives 0.60 as a minimum acceptable cronbach’s alpha level for a reliability test. Analytical tools such as descriptive statistic and ordinary least square method were used to analyse the data with the aid of SPSS version 23.

### RESULTS AND DISCUSSION

#### Tabulation and Analysis of Demographic Characteristics

*Table 1: Distribution of Respondents by Age Categories*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	21-34 years	69	23.0	23.0	23.0
	35-44 years	146	48.7	48.7	71.7
	45-54 years	85	28.3	28.3	100.0
	Total	300	100.0	100.0	

Source: *author’s computation aided by SPSS Version 23, 2025*

From Table 1, result respondents in the age category. Age 35 – 44 years bracket account for the highest responses in this category with 146 (48.7%) responses follow by Age 45 -54 years age bracket that account for 85 (28.3%) from total response according to age category. The least is

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respondents from 21-34 years age bracket with 69 (23.0%) of the total responses in the age category.

**Table 2** *Distribution of Respondents by Gender*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	152	50.7	50.7	50.7
	Female	148	49.3	49.3	100.0
	Total	300	100.0	100.0	

Source: *author's computation aided by SPSS Version 23, 2025*

Results from the Tables 2 aboveshow that a total number of 300 respondents completed the questionnaire. Male respondents are 152 (50.7%) while female are 148 (49.3%).

**Table 5:** *Distribution of Respondents by Business Experience*

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Less than 1 year	46	15.3	15.3	15.3
	1 - 2 years	46	15.3	15.3	21.0
	2 - 3 years	107	35.7	35.7	62.0
	over 3 years	101	33.7	33.7	100.0
	Total	300	100.0	100.0	

Source: *author's computation aided by SPSS Version 23, 2025*

From table 5, respondents of 2-3 years work experience account for highest responses in this category with 107(35.7%), follow by respondents with work experience of over 3 years with 101(33.7%) of the responses. While respondents with work experience of 1-2 years account for 46(15.3%) of the responses and respondents with less than 1 years experience had the least responses with 46(15.3%) of the responses received in this category

### Test of Hypothesis

**Table 6 :** *Result of Tests of Normality*

	Kolmogorov-Smirnov <sup>a</sup>			Shapiro-Wilk		
	Statistic	Df	Sig.	Statistic	Df	Sig.
Integration of Micro-finance analytics	.186	300	.130	.896	300	.065
Data driven decision	.199	300	.400	.831	300	.320

<b>Micro-finance analytics</b>	<b>.249</b>	<b>300</b>	<b>.080</b>	<b>.751</b>	<b>300</b>	<b>.156</b>
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Source: *author's computation aided by SPSS Version 23, 2025*

\*\*\* *p-value* < 0.01; \*\* *p-value*

The results reported in tables 6 provide strong evidence of normality of the distribution of the data, as the *Kolmogorov-Smirnov statistics* of **0.186** for **Integration of Micro-finance analytics**, **0.199** for **Data driven decision making** ;**0.249** for **micro-finance Analytics**; **0.187** are not significant at 1% and 5% levels. With these results, the null hypotheses of normal distributions of data cannot be rejected. This provides the basis for the use of parametric test for the study.

### Hypothesis one

H0<sub>1</sub>: The integration of Micro-finance analytics does not improve financial inclusion among underserved populations.

**Table 7. Regression Analysis for Microfinance Analytics and Financial Inclusion among underserved population's**

Variables	Coefficient	Std Error	T-Stat	Prob.
Constant (C)	1.235	0.232	3.208	0.000
Micro-finance Analytics	0.622	0.0342	6.347	0.017

**R: 0.936    R<sup>2</sup>: 0.852    F-statistic: 578.463**  
**Sig. (p-value): 0.000** Durbin-Watson statistics: 2.25

Source: *author's computation aided by SPSS Version 23, 2025*

\*\*\* *p-value* < 0.01; \*\* *p-value* < 0.05

Reported results in table 7 indicate a substantial statistical relationship between Micro-finance analytics and financial inclusion among underserved populations in iseyin area of Oyo state. This is because correlation value (R) of 0.936, which shows a very strong and positive linear relationship between variables. The Durbin-Watson statistic measures the evidence of autocorrelation in the residuals. The acceptable DW range of no autocorrelation is between 1.45 and 2.44. Thus, the fitted regression line result showed that there is no evidence of autocorrelation as indicated by DW statistic value of 2.25. The coefficient of determination (R<sup>2</sup>) of 0.852 indicates that approximately 85.2% of the variation in financial inclusion among underserved population in the study area can be explained by the extent of integration of Micro-finance Analytics. Just 14.8% of the variation can be attributed to other unmeasured or exogenous causes. According to the regression coefficient of (0.622), a one-unit increase in integration of Micro-finance Analytics is expected to increase financial inclusion among underserved populations by 62.2% when all other variables are held constant. Furthermore, the F statistic value of 578.463 with a matching significance level of 0.046 confirms the reliability and goodness-of-fit of the model. The p-value of the T-statistic is 0.017 which is statistically significant at 5% level of significant do not warrant the acceptance of the null hypothesis. In other words, *p-value* < .05 consequently, the null hypothesis that integration of Micro-finance analytics does not improve financial inclusion among underserved populations in iseyin area

of Oyo State is failed to be accepted.

**Hypothesis two**

H0<sub>2</sub>: Technological innovation does not significantly improve operational efficiencies.

**Table 8. Regression Analysis for Technological innovation and MFI Operational Efficiencies**

Variables	Coefficient	Std Error	T-Stat	Prob.
Constant (C)	0.980	0.623	5.612	0.034
Technological innovation	0.832	0.0510	6.712	0.013

**R: 0.901    R<sup>2</sup>: 0.722    F-statistic: 621.472**  
**Sig. (p-value): 0.0010    Durbin-Watson statistic: 1.92**

Source: *author’s computation aided by SPSS Version 23, 2025*

\*\*\* *p-value < 0.01*; \*\* *p-value < 0.05*

Reported results in table 8 indicate that a Technological innovation has significant impact on microfinance operational efficiencies. in iseyin area of Oyo state. This is because correlation value (R) of 0.901, which shows a very strong and positive linear relationship between variables. The Durbin-Watson statistic measures the evidence of autocorrelation in the residuals. The acceptable DW range of no autocorrelation is between 1.45 and 2.44. Thus, the fitted regression line result showed that there is no evidence of autocorrelation as indicated by DW statistic value of 1.92 The coefficient of determination (R<sup>2</sup>) of 0.722 indicates that approximately 72.2% of the variation in Micro-finance Operational efficiencies in the study area can be explained by the extent of data driven decision making. Just 27.8% of the variation can be attributed to other unmeasured or exogenous causes. According to the regression coefficient of (0.832), a one-unit increase in data driven decision is expected to increase Microfinance efficiencies by 83.2% when all other variables are held constant. Furthermore, the F statistic value of 621.472 with a matching significance level of 0.001 confirms the reliability and goodness-of-fit of the model. The p-value of the T-statistic is 0.013 which is statistically significant at 5% level of significant do not warrant the acceptance of the null hypothesis. In other words, *p-value <.05* consequently, the null hypothesis that Technological innovations does not significantly improve operational efficiencies of MFIs in iseyin area of Oyo State is failed to be accepted.

**Hypothesis three**

H0<sub>3</sub>: Data Driven Decision does not significantly impact customer experience and financial behaviour.

**Table 9. Regression Analysis for Data Driven Decision and customer experience and financial behavior**

Variables	Coefficient	Std Error	T-Stat	Prob.
Constant (C)	2.286	0.432	5.409	0.046
Data Driven Decision	0.522	0.0782	3.312	0.002

**R: 0.900    R<sup>2</sup>: 0.802    F-statistic: 412.483**

**Sig. (p-value): 0.000 Durbin-Watson statistic: 1.88**

Source: *author's computation aided by SPSS Version 23, 2025*

\*\*\* *p-value < 0.01*; \*\* *p-value < 0.05*

Reported results in table 9 indicate that Data Driven Decision have significant impact on customer experience and financial behavior in iseyin area of Oyo state. This is because correlation value (R) of 0.900, which shows a very strong and positive linear relationship between variables. The Durbin-Watson statistic measures the evidence of autocorrelation in the residuals. The acceptable DW range of no autocorrelation is between 1.45 and 2.44. Thus, the fitted regression line result showed that there is no evidence of autocorrelation as indicated by DW statistic value of 1.88. The coefficient of determination (R<sup>2</sup>) of 0.802 indicates that approximately 80.2% of the variation in customer experience and financial behavior in the study area can be explained by the extent of Micro-finance Analytics. Just 19.8% of the variation can be attributed to other unmeasured or exogenous causes. According to the regression coefficient of (0.522), a one-unit increase in Micro-finance Analytics is expected to increase customer experience and financial behavior by 52.2% when all other variables are held constant. Furthermore, the F statistic value of 412.483 with a matching significance level of 0.000 confirms the reliability and goodness-of-fit of the model. The p-value of the T-statistic is 0.002 which is statistically significant at 5% level of significant do not warrant the acceptance of the null hypothesis. In other words, *p-value < .05* consequently, the null hypothesis which state that Data Driven Decision does not significantly impact customer experience and financial behavior in iseyin area of Oyo State is failed to be accepted.

### **Discussion of Findings**

Results from hypothesis one provides evidence that Micro-finance analytics have significant impact on financial inclusion among underserved populations. The practical implication of this finding is that real time analytics flag early repayment slumps, allowing MFIs to intervening before loans turn delinquent, which protects both institution and clients. Also integrating analytics with mobile money or agent networks means services can reach remote villages without building costly brick and mortar branches. However, the economic implication of the finding is that more credit flowing to underserved entrepreneurs raises household income thereby reduces poverty. This finding appears surprising, especially considering Ashutosh M. (2024), MFIs have a positive influence on financial inclusion and development outcomes, including outreach to underserved populations, loan repayment rates and business creation..

In respect of hypothesis two, similar findings as hypothesis one were shown between Technological innovation and operational efficiencies of MFIs. This finding corroborate with the work of Klapper and Singer (2022), According to Klapper and Singer (2022), data analytics can be used to better analyze and identify unbanked people, boost financial literacy, improve credit scoring and risk assessment using alternative data sources, and create personalized financial solutions.

The practical implications of this finding is that it produces faster loan processing why reducing MFIs operating costs and better risk management are enhanced. The economic implication of this findings is that when MFIs reduce cost through data driven decision it lead to increase in profit, lowering default rate, increased financial inclusion and contribute to GDP of the economy why boosting job creation, it enhanced fiscal gain in form of higher tax revenue from thriving micro-businesses and lower social transfer outlay which will improve the public budget balance.

For hypothesis three, however, findings demonstrate that Data Driven Decision impact customer experience and financial behavior. This finding corroborate with Kabeer (2021) who stated that it is an important tool for development strategy, offering financial services to economically productive but disadvantaged members of society. According to Suri and Jack (2016), the unbanked now have substantially more financial assets made available by microfinance for financial inclusion that have been seen in Kenyan mobile money systems like M-Pesa. According to Klapper and Singer (2022), data analytics can be used to better analyze and identify unbanked people, boost financial literacy, improve credit scoring and risk assessment using alternative data sources, and create personalized financial solutions.

### CONCLUSION AND RECOMMENDATION

This study explored the intersection of microfinance analytics and the persistent challenges of achieving financial inclusion among underserved populations. Findings reveal that microfinance institutions (MFIs) are instrumental in extending financial services to low-income and marginalized groups, systemic issues such as inadequate data analytics capacity, regulatory constraints, digital illiteracy, and infrastructural limitations continue to hinder broader inclusion. The integration of advanced data analytics holds promise for tailoring financial products, improving risk assessment, and enhancing outreach; however, these tools are often underutilized. Holistic strategies combining technological innovation, policy reform, and capacity building are essential to address these gaps.

Based on the findings, the following recommendations were proffered

- i. Integrating lightweight's micro-finance analytics into MFIs loan processing workflow and make it the default decision support tool. These will include piloting a cloud based analytic engine, using the dashboard during clients' interview and setting clear Key performance index (KPI). The expected outcome of the implementation is that it will increase financial inclusion and high portfolio quality is maintained.
- ii. Leveraging the proven impact of technological innovation by building a lightweight digital platform that automats core MFIs processes such loan origination, repayment tracking and reporting. This is done by selecting a low cost, scalable solution; pilot it on one of the branch in the area.
- iii. Customized Financial Products: MFIs should leverage analytics to develop customer-centric products that reflect the specific needs of various underserved segments. Use of dashboard to flag high potential clients and offer them a tailored product like a smaller, shorter-term loan with flexible repayment date.

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