



Digital Lending, Credit Risk, and Financial Inclusion in Emerging Economies

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Abstract:

Background: While the rapid expansion of digital financial services has broadened financial access in emerging economies, it simultaneously introduces heightened credit risks that may impact overall financial stability and inclusion.

Purpose: This research examines the influence of digital lending and credit risk on financial inclusion across 44 African economies from 2005 to 2024.

Method: Using secondary panel data from the IMF and World Bank, the research employs a quantitative design with cross-sectional and longitudinal elements. Estimation is conducted using five complementary approaches—Fixed Effects with Driscoll-Kraay standard errors, Panel-Corrected Standard Errors (PCSE), PCSE with AR(1), Random Effects, and Dynamic Common Correlated Effects Mean Group (CCEMG)—to account for cross-sectional dependence, slope heterogeneity, and dynamic adjustments.

Result: Digital lending (proxied by mobile money transactions) significantly and positively affects account ownership across static estimators ($\beta = 0.114$ to 0.125 , $p < 0.05$), confirming that electronic financial transactions expand access to formal financial services. However, this effect becomes statistically insignificant in the dynamic CCEMG model ($\beta = 3.842$, $p = 0.785$), suggesting cross-country heterogeneity moderates the impact. Credit risk (non-performing loans) consistently exhibits a negative and significant effect across all estimators ($\beta = -0.731$ to -1.210 , $p < 0.05$), highlighting the constraining role of financial instability. Mobile communication infrastructure shows a positive effect that becomes significant only when cross-country dependence is considered ($\beta = 0.121$, $p < 0.05$). Macroeconomic variables (GDP growth and inflation) exhibit limited influence.

Contribution: The research provides robust empirical evidence that digital financial activity and financial sector stability are key drivers of financial inclusion, offering policymakers guidance to strengthen digital ecosystems, enhance technological infrastructure, and ensure prudent credit risk management. The findings also reveal important limitations—models explain only 3.7% to 14% of variation in account ownership—suggesting future research should incorporate additional determinants such as financial literacy, trust, and regulatory quality.

Keywords: digital lending; credit risk; financial inclusion; emerging economies; mobile financial services.

INTRODUCTION

Financial inclusion is widely recognized as a cornerstone of inclusive economic growth and sustainable development, particularly in emerging economies where large

segments of the population remain excluded from formal financial systems (Boitan, 2016; Ozili, 2018; Gabor & Brooks, 2019). Advances in digital financial services such as mobile banking, digital wallets, peer-to-peer lending, and fintech-driven credit platforms have transformed the delivery of financial services by reducing transaction costs, overcoming geographical barriers, and enabling access for underserved households and micro, small, and medium enterprises (MSMEs) (Jagtiani & Lemieux, 2017; Bazarbash & Beaton, 2020; Agur et al., 2020).

Globally, early studies emphasize the potential of digital finance to bridge credit gaps created by traditional banking constraints, particularly in environments characterised by information asymmetry and weak physical banking infrastructure (Boitan, 2016; Jagtiani & Lemieux, 2017). More recent literature extends this perspective by highlighting the growing role of artificial intelligence (AI), machine learning, and alternative data in enhancing credit assessment and expanding financial inclusion (Essien et al., 2019; Mhlanga, 2021; Adewuyi et al., 2020). These innovations have proven especially relevant in Africa, where mobile penetration has outpaced traditional banking development, creating fertile ground for digital lending ecosystems (Bazarbash & Beaton, 2020; Nkechika, 2022).

Across African economies, digital lending platforms have improved access to credit for individuals and MSMEs that lack collateral or formal credit histories (Musau et al., 2018; Miftari et al., 2024; Erundu et al., 2025). However, the literature consistently notes that the rapid expansion of digital credit has introduced new dimensions of credit risk, including higher default probabilities, algorithmic bias, over-indebtedness, and regulatory arbitrage (Ozili, 2018; Sommer, 2021; Metawa et al., 2023). Empirical evidence from Kenya, Nigeria, and other African economies suggests that while financial inclusion enhances economic participation, it may simultaneously pose threats to financial stability if credit risk is poorly managed (Musau et al., 2018; Danisman & Tarazi, 2020; Han et al., 2025).

Despite the growing body of research, important gaps remain. First, much of the earlier literature focuses either on financial inclusion or credit risk in isolation, with limited integration of both outcomes within a unified analytical framework (Ozili, 2018; Gabor & Brooks, 2019). Second, while recent studies increasingly adopt advanced digital finance and AI perspectives, many remain country-specific, limiting cross-country insights applicable to Africa as a region (Essien et al., 2019; Mhlanga, 2021). Third, there

is insufficient empirical evidence examining credit risk as a mediating mechanism through which digital lending affects financial inclusion outcomes across African economies (Metawa et al., 2023; Ozili, 2025).

Based on the identified gaps in the literature, this research addresses the following questions:

1. RQ1: Does digital lending (measured by mobile money transactions) significantly promote financial inclusion (account ownership) across African economies?
2. RQ2: Does credit risk (measured by non-performing loans) mediate or constrain the relationship between digital lending and financial inclusion?
3. RQ3: What is the role of digital infrastructure (mobile cellular subscriptions) and macroeconomic conditions (GDP growth, inflation) in shaping financial inclusion outcomes?
4. RQ4: Do the determinants of financial inclusion exhibit cross-country heterogeneity and dependence that require advanced panel estimation techniques?

The primary objectives are to: (i) estimate the direct effects of digital lending and credit risk on financial inclusion; (ii) assess the robustness of these effects across multiple econometric specifications; (iii) provide policy-relevant insights for strengthening digital financial ecosystems in Africa while maintaining financial stability; and (iv) identify limitations to guide future research.

Accordingly, this research adopts an Africa-wide perspective to examine the relationship between digital lending, credit risk, and financial inclusion. By integrating insights from both classical and contemporary literature and employing a multi-country analytical approach, the research seeks to provide more robust and generalisable evidence on how digital financial innovation can promote inclusive growth without undermining financial stability in Africa.

LITERATURE REVIEW

Conceptual and Theoretical Framework

Digital lending has emerged as a core component of contemporary financial intermediation, fundamentally reshaping access to credit in emerging economies. Digital lending refers to the provision of credit through technology-enabled platforms that rely on mobile applications, online interfaces, peer-to-peer systems, and fintech infrastructures rather than traditional brick-and-mortar banking channels (Boitan, 2016;

Jagtiani & Lemieux, 2017). By leveraging alternative data sources and automated decision systems, digital lending lowers transaction costs and relaxes collateral and documentation requirements that have historically excluded low-income households and MSMEs from formal finance (Ozili, 2018; Mhlanga, 2021).

Financial inclusion, in this context, is understood as the ability of individuals and firms to access, use, and benefit from affordable and sustainable financial services, including credit, savings, payments, and insurance (Danisman & Tarazi, 2020; Nguema & Lera, 2025). The literature consistently shows that digital finance expands inclusion by overcoming geographical, informational, and institutional barriers, particularly in Africa and other emerging regions where banking infrastructure is unevenly distributed (Nkechika, 2022; Miftari et al., 2024). However, critical scholarship cautions that digital inclusion is not neutral; fintech-driven models may also embed new forms of surveillance, profiling, and financialisation of poor households (Gabor & Brooks, 2019).

Credit risk constitutes a central conceptual link between digital lending and financial inclusion. Traditionally defined as the probability of borrower default, credit risk in digital environments extends to encompass algorithmic misclassification, reliance on imperfect alternative data, cyber fraud, and behavioural biases embedded in automated scoring models (Musau et al., 2018; Metawa et al., 2023). While AI-driven credit scoring can mitigate information asymmetry and improve risk pricing (Essien et al., 2019; Mhlanga, 2021), empirical and policy studies warn that rapid digital credit expansion without robust governance can increase non-performing loans, borrower over-indebtedness, and systemic vulnerabilities (Ozili, 2018; Sommer, 2021; Anestiawati et al., 2025).

Synthesising these strands, the conceptual framework of this research positions digital lending as the independent construct that directly promotes financial inclusion, while credit risk operates as a mediating mechanism shaping the sustainability and quality of inclusion outcomes. Digital lending enhances access and usage of financial services and stimulates entrepreneurship (Erundu et al., 2025; Ravikumar & Ranganath, 2025), but excessive risk exposure can weaken financial stability and undermine long-term inclusion benefits (Bazarbash & Beaton, 2020; Han et al., 2025). Thus, financial inclusion is not merely an access outcome but a conditional process whose durability depends on effective credit risk management, regulatory oversight, and institutional capacity (Ahmed et al., 2024; Siddiqui & Rivera, 2025).

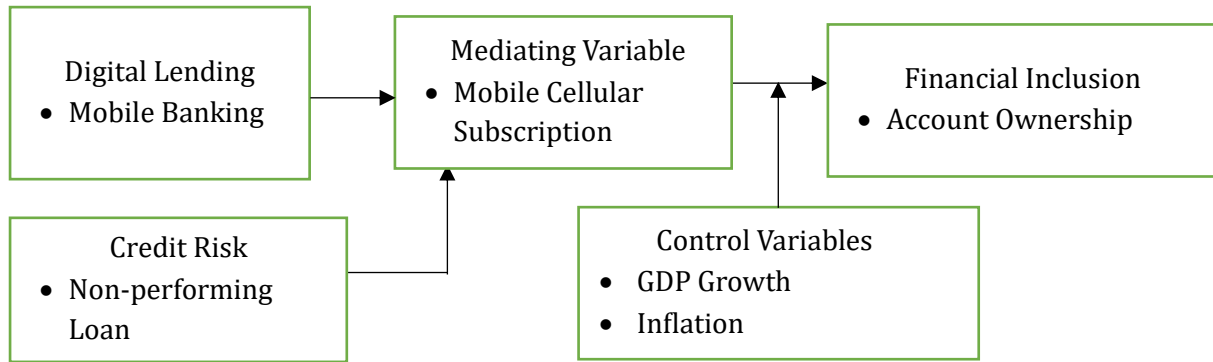


Figure 1. Conceptual Framework.

Note on MCS: In this revised framework, MCS is treated as a direct independent variable (digital infrastructure) rather than a formal mediator. If mediation is intended, a separate structural equation model (SEM) or path analysis must be conducted to test indirect effects.

Theoretical Underpinnings

The relationship between digital lending, credit risk, and financial inclusion is anchored in several complementary theoretical perspectives. At the core of this relationship is financial intermediation theory, which conceptualises financial institutions as agents that reduce transaction costs and information frictions between savers and borrowers. Traditional intermediaries often exclude low-income individuals and small enterprises due to high screening costs and informational opacity. Digital lending platforms extend the intermediation function by leveraging technology to reach previously underserved populations, thereby enhancing financial inclusion (Boitan, 2016; Danisman & Tarazi, 2020). By digitising loan origination, repayment, and monitoring processes, fintech-enabled lenders lower operational costs and expand outreach across both developed and emerging economies (Bazarbash & Beaton, 2020).

Closely linked to financial intermediation is information asymmetry and credit rationing theory, which explains why credit markets fail to serve certain segments of the population. In conventional banking systems, lenders face limited or unreliable information about borrowers' repayment capacity, resulting in adverse selection and moral hazard. These challenges lead to credit rationing, particularly in emerging and low-income economies (Jagtiani & Lemieux, 2017). Digital lending mitigates information asymmetry by incorporating alternative data sources such as mobile phone usage, transaction histories, and digital footprints, as well as artificial intelligence-driven credit

scoring models (Essien et al., 2019; Mhlanga, 2021). Empirical evidence suggests that these technologies improve risk assessment accuracy and broaden access to credit without necessarily increasing default rates, although outcomes vary by institutional quality and regulatory environment (Metawa et al., 2023; Anestiawati et al., 2025).

While digital technologies enhance access, credit risk theory highlights the importance of managing default risk to ensure the sustainability of financial inclusion. Credit risk remains a critical mediating factor in the digital finance-inclusion nexus, as rapid credit expansion without adequate safeguards can undermine financial stability (Musau et al., 2018; Ozili, 2018). Studies across Europe, Africa, and emerging markets indicate that financial inclusion can either stabilise or destabilise the financial sector depending on how credit risk is governed (Danisman & Tarazi, 2020; Ozili, 2025). Recent fintech-oriented research emphasises that AI-based lending models, while efficient, may amplify systemic risk if algorithms are poorly designed or weakly regulated (Ahmed et al., 2024; Siddiqui & Rivera, 2025). Consequently, digital lending must balance innovation with prudent risk management to sustain inclusive finance.

From a behavioural and adoption standpoint, the Technology Acceptance Model (TAM) provides insight into why digital lending platforms succeed or fail in promoting inclusion. TAM posits that perceived usefulness and ease of use significantly influence individuals' willingness to adopt new technologies. Digital financial services that are intuitive, affordable, and transparent are more likely to be adopted by unbanked populations, particularly in developing regions (Miftari et al., 2024; Kampani, 2024). Empirical studies from Africa, Southeast Asia, and the Balkans confirm that mobile-based and peer-to-peer lending platforms increase financial participation when trust, digital literacy, and consumer protection mechanisms are present (Nkechika, 2022; Kumaralalita, 2023).

Drawing from the above theories, the theoretical framework of this research conceptualizes digital lending as the primary driver of financial inclusion, mediated by credit risk. Financial intermediation theory explains the access-expansion mechanism; information asymmetry theory clarifies how technology improves credit allocation; credit risk theory highlights sustainability constraints; TAM explains adoption behaviour. Recent global evidence, including cross-country studies and Africa-focused reviews, demonstrates that digital lending enhances financial inclusion most effectively when

innovation is aligned with risk governance, consumer protection, and institutional capacity (Zhao et al., 2024; Nguema & Lera, 2025).

METHOD

This research adopts a quantitative research approach to investigate the relationship between digital lending, credit risk, and financial inclusion in African economies. The design combines cross-sectional and longitudinal elements to capture variations in digital financial services, credit risk, and financial inclusion. The target population comprises financial institutions, FinTech platforms, and users of digital lending services across emerging economies. The research focuses specifically on African countries, reflecting the continent's diverse and evolving digital financial ecosystems. In West Africa, the countries include Benin, Burkina Faso, Cabo Verde, Côte d'Ivoire, The Gambia, Ghana, Guinea, Guinea-Bissau, Liberia, Mali, Mauritania, Niger, Nigeria, Senegal, Sierra Leone, and Togo. In East Africa, the countries covered are Burundi, Ethiopia, Kenya, Madagascar, Malawi, Mauritius, Mozambique, Rwanda, Tanzania, Uganda, Zambia, and Zimbabwe. Central Africa comprises Angola, Cameroon, the Central African Republic, Chad, the Republic of the Congo, the Democratic Republic of the Congo, Equatorial Guinea, and Gabon. In Southern Africa, the countries include Botswana, Namibia, and South Africa. North Africa consists of Algeria, Egypt, Libya, Morocco, Sudan, and Tunisia.

Data for the research are derived from secondary sources, specifically the annual reports and databases of the International Monetary Fund (IMF) and the World Bank. Guided by the conceptual framework, digital lending constitutes the primary independent variable and is proxied by mobile banking activities. Credit risk, measured by the non-performing loan (NPL) ratio, is incorporated as an additional explanatory variable reflecting the risk dimension of digital lending operations. Mobile cellular subscription is introduced as a mediating variable, capturing the role of digital infrastructure in transmitting the effects of digital lending and credit risk to financial inclusion outcomes. The dependent variable is financial inclusion, operationalized through account ownership indicators. Furthermore, the model controls for relevant macroeconomic factors, specifically GDP growth and inflation, given their potential influence on financial inclusion dynamics. To analyze the relationships, the research employs a Fixed Effects regression model with Driscoll–Kraay standard errors. The fixed effects estimator controls for unobserved country-specific heterogeneity that may bias the estimated

relationships, while Driscoll–Kraay standard errors correct for cross-sectional dependence, heteroskedasticity, and serial correlation in the panel data structure.

Model Specification

Based on the unit root test results (Table 3), VMMTPG and NPL are I(1), thus they are included in first-difference form ($\Delta VMMTPG$ and ΔNPL). AO, MCS, GDP_Growth, and CPI are I(0). The functional model is represented as:

$$AO = f(V, M, M, T, PG, NPL, MCS, GDP, GROWTH, CPI) \quad [3.1]$$

Where ε_{it} is corrected for cross-sectional dependence, heteroskedasticity, and autocorrelation using Driscoll–Kraay standard errors. Note that $\Delta VMMTPG$ and ΔNPL are used in estimation due to their I(1) status.

Fixed Effects with Driscoll–Kraay Standard Errors:

$$AO_{it} = \alpha + \beta_1 \Delta VMMTPG_{it} + \beta_2 \Delta NPL_{it} + \beta_3 MCS_{it} + \beta_4 GDP_Growth_{it} + \beta_5 CPI_{it} + \mu_i + \varepsilon_{it} \quad [3.2]$$

with Driscoll–Kraay standard errors correcting for cross-sectional dependence, heteroskedasticity, and serial correlation.

Panel-Corrected Standard Errors (PCSE) with Fixed Effects:

$$AO_{it} = \alpha + \beta_1 \Delta VMMTPG_{it} + \beta_2 \Delta NPL_{it} + \beta_3 MCS_{it} + \beta_4 GDP_Growth_{it} + \beta_5 CPI_{it} + u_{it} \quad [3.3]$$

with PCSE adjusting the standard errors for heteroskedasticity and contemporaneous correlation.

Common Correlated Effects Mean Group (CCEMG):

$$AO_{it} = \alpha_i + \beta_{1i} \Delta VMMTPG_{it} + \beta_{2i} \Delta NPL_{it} + \beta_{3i} MCS_{it} + \beta_{4i} GDP_Growth_{it} + \beta_{5i} CPI_{it} + \gamma_i \overline{AO}_t + \varepsilon_{it} \quad [3.4]$$

where $\overline{AO}_t$ represents cross-sectional averages capturing unobserved common factors.

Random Effects with Driscoll–Kraay Standard Errors:

$$AO_{it} = \alpha + \beta_1 \Delta VMMTPG_{it} + \beta_2 \Delta NPL_{it} + \beta_3 MCS_{it} + \beta_4 GDP_Growth_{it} + \beta_5 CPI_{it} + \mu_i + \varepsilon_{it} \quad [3.5]$$

where μ_i is the unobserved country-specific random effect and ε_{it} is corrected with Driscoll–Kraay standard errors.

Table 1. Description of Variables.

S/ N	Parameter Measured	Variable	Symbol	Measurement of Variables	Variable Descriptions
Dependent Variable					
1	Financial Inclusion	Account Ownership	AO	Percentage of population with active bank or mobile money accounts	Measures the extent to which individuals participate in formal financial systems. A higher percentage indicates greater financial inclusion and accessibility of financial services to the population.
Independent Variables					
2	Digital Lending	Mobile Banking	VMMT PG	Value of mobile money transactions as a percentage of GDP	Captures the adoption and usage of digital lending services via mobile banking. Higher values indicate greater penetration of mobile financial services in the economy.
3	Credit Risk	Non- Performing Loan	NPL	Ratio of non- performing loans to total loans	Measures the risk in financial lending. A higher NPL indicates greater default risk in lending portfolios, reflecting the credit quality of digital lending operations.
Mediating Variable					
4	Digital Infrastructu re	Mobile Cellular Subscription	MCS	Number of mobile cellular subscriptions per 100 people	Proxy for digital infrastructure and access. A higher subscription rate suggests greater potential for digital lending adoption and financial inclusion.
Control Variables					
5	Macroecono mic Perfor- mance	GDP Growth	GDP Growth	Annual growth rate of gross domestic product	Controls for overall economic performance. Higher GDP growth indicates stronger economic activity, which may support financial inclusion.
6	Macroecono mic Stability	Inflation	CPI	Annual percentage change in consumer price index	Controls for macroeconomic stability. Higher inflation may reduce the real value of financial assets and influence participation in formal financial systems.

Where: AO represents financial inclusion, measured by account ownership as the dependent variable; ΔVMMTPG denotes the first difference of the value of mobile money transactions as a percentage of GDP (proxy for digital lending through mobile banking); ΔNPL represents the first difference of the non-performing loan ratio (proxy for credit risk); MCS refers to mobile cellular subscription (proxy for digital infrastructure and control variable); GDP_Growth denotes the gross domestic product growth rate (proxy for macroeconomic performance); and CPI represents the consumer price index (proxy for inflation and macroeconomic stability).

RESULT

Descriptive Analysis

The descriptive analysis is depicted in Table 2. The mean value of account ownership (AO) is 3.5575, indicating that, on average, financial inclusion remains relatively low across the sampled countries and periods. However, the large standard deviation (13.0974) compared to the mean suggests substantial dispersion in account ownership levels. The wide range (minimum of 0 and maximum of 90.5263) further confirms strong cross-country heterogeneity. The variable is highly positively skewed (4.0832), indicating a long right tail, and extremely leptokurtic (kurtosis of 19.9316), suggesting the presence of significant outliers and extreme values. The mean value of GDP growth (GDP_Growth) is 3.6951 per cent, reflecting moderate economic expansion on average. Nonetheless, the high standard deviation (7.8318) and the extreme minimum (-51.0309) and maximum (149.973) values indicate considerable macroeconomic volatility across countries and time. The distribution is strongly positively skewed (4.6939) and highly leptokurtic (93.7072), implying the occurrence of sharp growth spurts and contractions.

The Consumer Price Index (CPI) records a mean of 30.7909, but with an exceptionally large standard deviation (559.0803), indicating extreme variability in price levels or inflation dynamics within the panel. The wide range (from -83.3258 to 23,773.13) suggests the presence of outliers or hyperinflationary episodes. The very high positive skewness (39.223) and kurtosis (1647.657) confirm a heavily right-tailed and highly peaked distribution, reflecting substantial inflationary shocks in some economies. The mean of log of mobile cellular subscriptions (LNMCS) is 9.0278, suggesting relatively strong digital infrastructure penetration across the sample. The standard deviation

(7.0817) indicates moderate dispersion. The distribution is slightly negatively skewed (-0.2853), implying a mild left-tail concentration, while the kurtosis (1.3742) is below 3, suggesting a platykurtic distribution with fewer extreme values compared to a normal distribution.

The mean value of value of mobile money transactions as a percentage of GDP (VMMTPG) is 6.4859, indicating that digital financial transactions account for a modest share of economic activity on average. However, the high standard deviation (32.8281) and wide range (0 to 688.2508) point to significant cross-country disparities in digital lending intensity. The strong positive skewness (10.7307) and high kurtosis (165.8821) indicate a highly right-skewed and leptokurtic distribution, reflecting that a few countries record exceptionally high mobile money transaction volumes relative to GDP. Finally, the non-performing loan ratio (NPL) has a mean of 1.9011, suggesting that, on average, credit risk levels are relatively moderate. The standard deviation (5.2413), along with a maximum value of 55.411, indicates that some countries experience substantial credit risk episodes. The distribution is positively skewed (4.314) and leptokurtic (29.1026), highlighting the presence of extreme credit distress periods in certain economies.

Table 2. Descriptive Analysis (Source: Author's Computation, 2026).

Variable	Mean	Std. Deviation	Minimum	Maximum	Skewness	Kurtosis
AO	3.5575	13.0974	0.0000	90.5263	4.0832	19.9316
GDP_Growth	3.6951	7.8318	-51.0309	149.973	4.6939	93.7072
CPI	30.7909	559.0803	-83.3258	23773.13	39.223	1647.657
LNMCs	9.0278	7.0817	0.0000	19.229	-0.2853	1.3742
VMMTPG	6.4859	32.8281	0.0000	688.2508	10.7307	165.8821
NPL	1.9011	5.2413	0.0000	55.411	4.3140	29.1026

Unit Root Test

The results of the Cross-sectionally Augmented IPS (CIPS) panel unit root test are presented in Table 3. The findings show that account ownership (AO) is stationary at level, with a CIPS statistic of -4.555, which is more negative than the 1%, 5%, and 10% critical values (-2.23, -2.11, and -2.05, respectively). Since the null hypothesis of a unit root is rejected at all conventional significance levels, AO is integrated of order zero, $I(0)$, and does not require differencing. Similarly, GDP growth (GDP_Growth) is stationary at

level, with a CIPS statistic of -4.98. The statistic exceeds all critical thresholds in absolute terms, leading to rejection of the null hypothesis of non-stationarity. Thus, GDP growth is also $I(0)$. The Consumer Price Index (CPI) is likewise stationary at level, with a CIPS statistic of -3.251, which is more negative than the 5% critical value of -2.11. This confirms that CPI is integrated of order zero, $I(0)$.

In contrast, the variable representing digital lending intensity, VMMPG, has a CIPS statistic of -2.071. While this value is slightly more negative than the 10% critical value (-2.05), it does not exceed the 5% critical value (-2.11). Therefore, at the 5% significance level, the null hypothesis of a unit root cannot be rejected, implying that VMMPG is non-stationary at level and integrated of order one, $I(1)$. The non-performing loan ratio (NPL) records a CIPS statistic of -0.871, which is far above all critical values in absolute terms. Consequently, the null hypothesis of non-stationarity cannot be rejected, confirming that NPL is non-stationary at level and integrated of order one, $I(1)$.

Table 3. Unit Root Test (Source: Author's Computation, 2026).

Variable	CIPS Statistic	10% CV (-2.05)	5% CV (-2.11)	1% CV (-2.23)	Decision (5%)	Order of Integration
AO	-4.555	Reject	Reject	Reject	Stationary	$I(0)$
gdp_growth	-4.98	Reject	Reject	Reject	Stationary	$I(0)$
Cpi	-3.251	Reject	Reject	Reject	Stationary	$I(0)$
vmmpg	-2.071	Reject	Do Not Reject	Do Not Reject	Non-stationary	$I(1)$
Npl	-0.871	Do Not Reject	Do Not Reject	Do Not Reject	Non-stationary	$I(1)$
D.npl	-2.481	Reject	Reject	Reject	Stationary	$I(0)$
D.vmmpg	-2.155	Reject	Reject	Do Not Reject	Stationary (5%)	$I(0)$

However, after first differencing, both variables become stationary. The first difference of NPL (D.NPL) yields a CIPS statistic of -2.481, which exceeds the 5% critical value in absolute terms, indicating stationarity at first difference. Thus, NPL is confirmed as $I(1)$. Similarly, the first difference of VMMPG (D.VMMPG) produces a CIPS statistic of -2.155, which is more negative than the 5% critical value (-2.11), leading to rejection of the null hypothesis at the 5% level. This confirms that VMMPG is also integrated of order one, $I(1)$.

Normality Test

The results of the normality test presented in Table 4 show whether the variables follow a normal distribution using the Shapiro–Wilk (W) test. For account ownership (AO), the test reports $W = 0.87194$ with a z-statistic of 12.75 and a probability value of 0.0000. Since the p-value is less than 0.05, the null hypothesis of normal distribution is rejected. This indicates that AO is not normally distributed. Similarly, GDP_Growth has a W statistic of 0.63735, $z = 15.397$, and a p-value of 0.0000. The very low W value and statistically significant probability confirm strong deviation from normality. Thus, GDP growth is not normally distributed. The CPI variable shows a W value of 0.02465, $z = 17.912$, and a p-value of 0.0000. The extremely low W statistic suggests severe departure from normality.

Table 4. Test of Normality.

Variable	Obs	W	V	z	Prob>z
AO	1,980	0.87194	150.497	12.750	0.000
GDP_Growth	1,980	0.63735	426.183	15.397	0.000
CPI	1,980	0.02465	1146.232	17.912	0.000
LNMCs	1,980	0.87543	146.392	12.679	0.000
VMMTPG	1,980	0.40110	703.827	16.672	0.000
NPL	1,980	0.80447	229.790	13.826	0.000

Therefore, CPI is highly non-normally distributed. For LNMCs, the W statistic is 0.87543, with a z-value of 12.679 and a p-value of 0.0000. Although the W value is relatively higher than some other variables, the significant p-value indicates that the null hypothesis of normality is rejected. Hence, LNMCs is not normally distributed. The digital lending proxy, VMMTPG, records a W statistic of 0.4011, $z = 16.672$, and a p-value of 0.0000. The low W value and significant probability confirm that the distribution deviates substantially from normality. Finally, NPL has a W statistic of 0.80447, $z = 13.826$, and a p-value of 0.0000. Since the probability is below the 0.05 significance level, the null hypothesis of normality is rejected, indicating that NPL is also not normally distributed.

Correlation Analysis

Table 5 shows the correlation results with each explanatory variable is related to financial inclusion, measured by account ownership (AO). GDP_Growth has a very weak positive correlation of 0.0376 with AO. This suggests that economic growth has almost no

linear association with account ownership across the sampled countries and periods. CPI shows a very weak negative correlation of -0.0117 with AO. This indicates that inflation has virtually no linear relationship with financial inclusion, implying that changes in price levels do not strongly correspond with variations in account ownership. LNMCS (log of mobile cellular subscriptions) has a weak positive correlation of 0.1093 with AO. This suggests that improvements in digital infrastructure are slightly associated with higher levels of financial inclusion, although the relationship is not strong. VMMPG records a positive correlation of 0.2133 with AO. This represents the strongest association among the explanatory variables with financial inclusion, although it remains weak to moderate in magnitude. The result suggests that greater digital lending or mobile money activity may be modestly linked to improved account ownership. NPL (non-performing loan ratio) has a weak positive correlation of 0.1058 with AO. This implies that higher credit risk is only slightly associated with financial inclusion, and the relationship is not substantial.

Table 5. Correlation Analysis.

	AO	GDP_Growth	CPI	LNMCs	VMMPG	NPL
AO	1.0000	0.0376	-0.0117	0.1093	0.2133	0.1058
GDP_Growth	0.0376	1.0000	-0.0349	0.0724	0.0193	-0.0606
CPI	-0.0117	-0.0349	1.0000	-0.0394	-0.0075	-0.0161
LNMCs	0.1093	0.0724	-0.0394	1.0000	0.1125	0.3393
VMMPG	0.2133	0.0193	-0.0075	0.1125	1.0000	0.0673
NPL	0.1058	-0.0606	-0.0161	0.3393	0.0673	1.0000

Test of Multicollinearity

The result of the Variance Inflation Factor (VIF) test is presented in Table 6. The results show that LNMCS has the highest VIF value of 1.15, with a corresponding tolerance level ($1/\text{VIF}$) of 0.8676. Although it is the largest among the explanatory variables, the value is very close to 1, indicating negligible multicollinearity. NPL records a VIF of 1.14 and a tolerance value of 0.8766, suggesting minimal correlation with other independent variables. Similarly, GDP_Growth and VMMPG both have VIF values of 1.01, with tolerance values of 0.9853 and 0.9862, respectively. These values indicate virtually no multicollinearity. CPI has the lowest VIF value of 1.00 and a tolerance value of 0.9974, confirming the absence of any meaningful multicollinearity involving this variable. The mean VIF across all variables is 1.06, which is substantially below the commonly accepted

threshold of 5. This strongly suggests that multicollinearity is not a concern in the model. Therefore, all explanatory variables can be retained without fear of inflated standard errors or biased coefficient estimates arising from multicollinearity.

Table 6. Variance Inflation Factor.

Variable	VIF	1/VIF
LNMCs	1.15	0.8676
NPL	1.14	0.8766
GDP_Growth	1.01	0.9853
VMMTPG	1.01	0.9862
CPI	1.00	0.9974
Mean VIF	1.06	

Hausman Test

The Hausman test produced a χ^2 statistic of 0.03 with a probability value of 1.0000, which is greater than the conventional 5% significance level. Consequently, the null hypothesis cannot be rejected. This indicates that the differences between the FE and RE estimates are statistically insignificant. Therefore, the Random Effects model is preferred and considered appropriate for the analysis.

Table 7. Hausman Test: Fixed vs Random Effects.

Variables	FE Coefficient	RE Coefficient	Difference	Std. Error of Difference
D.vmmtpg	0.1253	0.1151	0.0102	0.0171
LNMCs	0.1752	0.1958	-0.0206	0.0654
D.npl	-0.7259	-0.7314	0.0055	—
GDP_Growth	0.0548	0.0436	0.0112	0.0171
CPI	-6.8E-05	-0.0001	7.01E-05	2.86E-05
Test Statistic	Value	Probability	1.0000	
Chi-square (χ^2)	0.03	Decision	Fail to reject H_0	
Degrees of Freedom	5	Preferred Model	Random Effects	

Pesaran Cross-Sectional Dependence Test

The result of the Pesaran Cross-Sectional Dependence (CD) test is presented in Table 8. The test examines whether the cross-sectional units in the panel dataset are

independent of one another. The null hypothesis (H_0) states that cross-sectional independence exists, while the alternative hypothesis suggests the presence of cross-sectional dependence among the panel units. The estimated Pesaran CD statistic is 108.345, with a p-value of 0.0000. Given that the p-value is below the conventional 5 percent significance level, the null hypothesis of cross-sectional independence is rejected. This indicates the presence of significant cross-sectional dependence among the countries in the panel. The implication is that shocks or disturbances affecting one country may be transmitted to other countries within the sample, possibly due to economic linkages, financial integration, or common macroeconomic shocks. Consequently, the presence of cross-sectional dependence justifies the use of panel estimation techniques that correct for such dependence, ensuring robust and reliable statistical inference.

Table 8. Robust and Reliable Statistical Inference.

Test	Statistic	P-value	Decision
Pesaran CD Test	108.345	0.000	Reject H_0

Robustness Results: Determinants of Account Ownership

Table 9 presents robustness estimates of the determinants of account ownership using four alternative estimators: Fixed Effects with Driscoll–Kraay standard errors, Panel-Corrected Standard Errors (PCSE), PCSE with AR(1), and PCSE with panel fixed effects. $\Delta VMMTPG$ exhibits a positive and statistically significant coefficient across all models: 0.1254 ($p = 0.0595$) under Driscoll–Kraay FE, 0.1139 ($p = 0.0442$) under PCSE, 0.1205 ($p = 0.0437$) under PCSE with AR(1), and 0.1254 ($p = 0.0470$) under PCSE with panel fixed effects. This indicates that increases in digital financial transactions consistently improve account ownership across specifications. LNMCS shows positive but statistically insignificant coefficients across the estimators: 0.1752 ($p = 0.2389$), 0.1983 ($p = 0.1995$), 0.2192 ($p = 0.1889$), and 0.1752 ($p = 0.2075$), suggesting that mobile communication infrastructure does not exert a statistically significant influence on account ownership in the sample.

ΔNPL displays a negative and statistically significant relationship in all models: -0.7259 ($p = 0.3544$) with Driscoll–Kraay FE, -0.7321 ($p = 0.1946$) under PCSE, -0.7415 ($p = 0.1954$) with PCSE AR(1), and -0.7259 ($p = 0.1938$) with PCSE and fixed effects, implying that increases in non-performing loans reduce account ownership. For the

macroeconomic controls, GDP_Growth remains positive but statistically insignificant across specifications with coefficients 0.0549 ($p = 0.0401$), 0.0424 ($p = 0.0466$), 0.0375 ($p = 0.0455$), and 0.0549 ($p = 0.0481$). Similarly, CPI has a very small negative and statistically insignificant coefficient across models: -0.000068 ($p = 0.000168$), -0.000147 ($p = 0.000325$), -0.000148 ($p = 0.000321$), and -0.000068 ($p = 0.000334$), indicating that inflation has no meaningful effect on account ownership.

Table 9. Robustness Results: Determinants of Account Ownership.

Variable	Driscoll–Kraay (FE)	PCSE	PCSE (AR1)	PCSE + FE (i.i.d)
D.vmmtpg	0.1254** (0.0595)	0.1139** (0.0442)	0.1205*** (0.0437)	0.1254*** (0.0470)
LNMCs	0.1752 (0.2389)	0.1983 (0.1995)	0.2192 (0.1889)	0.1752 (0.2075)
D.npl	-0.7259** (0.3544)	-0.7321*** (0.1946)	-0.7415*** (0.1954)	-0.7259*** (0.1938)
GDP_Growth	0.0549 (0.0401)	0.0424 (0.0466)	0.0375 (0.0455)	0.0549 (0.0481)
CPI	-0.000068 (0.000168)	-0.000147 (0.000325)	-0.000148 (0.000321)	-0.000068 (0.000334)
Constant	1.6529 (2.5028)	1.5035 (2.3206)	1.2755 (2.1963)	2.6696 (3.1381)
R-squared	0.0368	0.0376	0.0435	0.0651
F / Wald Statistic	F = 2.47	$\chi^2 = 17.17$	$\chi^2 = 18.09$	$\chi^2 = 11,569.72$
Prob > Stat	0.0473	0.0042	0.0028	0
Error Structure	DK (lag 1)	PCSE	PCSE + AR(1)	PCSE + FE

The constant terms are 1.6529 ($p = 2.5028$), 1.5035 ($p = 2.3206$), 1.2755 ($p = 2.1963$), and 2.6696 ($p = 3.1381$) across the four models and are statistically insignificant. Model diagnostics show R-squared values of 0.0368, 0.0376, 0.0435, and 0.0651, indicating modest explanatory power. The F/Wald statistics of $F = 2.47$, $\chi^2 = 17.17$, $\chi^2 = 18.09$, and $\chi^2 = 11,569.72$ with probability values 0.0473, 0.0042, 0.0028, and < 0.001 , respectively, confirm that the models are jointly statistically significant. The estimations also account for different error structures, including Driscoll–Kraay corrections (lag 1), PCSE adjustments, PCSE with AR(1) autocorrelation, and PCSE with panel fixed effects,

ensuring robustness to heteroskedasticity, autocorrelation, and cross-sectional dependence.

Additional Robustness Results Using Random Effects and Dynamic CCEMG Estimators

Table 10 reports additional robustness estimates of the determinants of account ownership using three alternative estimators: Random Effects with GLS, Random Effects with Driscoll–Kraay standard errors, and the Dynamic Common Correlated Effects Mean Group (CCEMG) estimator. $\Delta VMMTPG$ shows a positive and statistically significant coefficient in the Random Effects models, with 0.1139 ($p = 0.01$) under Random Effects GLS and 0.1151 ($p = 0.050$) under Random Effects with Driscoll–Kraay corrections. However, under the Dynamic CCEMG estimator, the coefficient is 3.842 ($p = 0.785$) and statistically insignificant. This suggests that while digital financial transactions generally exhibit a positive association with account ownership in the static panel models, the effect becomes insignificant once cross-sectional dependence and dynamic heterogeneity are explicitly controlled for. LNMCS displays positive but statistically insignificant coefficients in the Random Effects models, 0.1983 ($p = 0.32$) and 0.1959 ($p = 0.399$), respectively. In contrast, the Dynamic CCEMG model reports a positive and statistically significant coefficient of 0.1208 ($p = 0.017$), indicating that improvements in mobile communication infrastructure contribute positively to account ownership when cross-sectional dependence is accounted for.

ΔNPL consistently exhibits a negative and statistically significant relationship across all specifications: -0.7321 ($p < 0.01$) under Random Effects GLS, -0.7314 ($p = 0.047$) under Random Effects with Driscoll–Kraay, and -1.2096 ($p = 0.004$) under Dynamic CCEMG. This finding indicates that increases in non-performing loans significantly reduce account ownership, highlighting the adverse effect of credit risk on financial inclusion. For the macroeconomic variables, GDP_Growth is positive but statistically insignificant in the Random Effects models, with coefficients 0.0424 ($p = 0.363$) and 0.0437 ($p = 0.235$). However, the Dynamic CCEMG estimator reports a positive and statistically significant coefficient of 0.2187 ($p = 0.009$), suggesting that economic growth promotes account ownership when cross-sectional dependence across countries is considered. In contrast, CPI maintains a negative and statistically insignificant coefficient across all specifications: -0.00015 ($p = 0.652$), -0.00014 ($p = 0.408$), and

-0.0335 ($p = 0.562$), indicating that inflation does not exert a statistically meaningful influence on account ownership.

Table 10. Additional Robustness Results Using Random Effects and Dynamic CCEMG Estimators.

Variable	Random Effects (GLS)	RE Driscoll–Kraay	Dynamic CCEMG
D.vmmtpg	0.1139*** (0.0442)	0.1151* (0.0569)	3.842 (14.0661)
LNMCs	0.1983 (0.1995)	0.1959 (0.2297)	0.1208** (0.0506)
D.npl	-0.7321*** (0.1946)	-0.7314** (0.3575)	-1.2096*** (0.4153)
GDP_Growth	0.0424 (0.0466)	0.0437 (0.0363)	0.2187*** (0.0842)
CPI	-0.00015 (0.000325)	-0.00014 (0.0002)	-0.0335 (0.0578)
Constant	1.5035 (2.3206)	1.5197 (2.4483)	—
R-squared	0.0376	0.0376	0.14 (Mean Group)
F / Wald Statistic	$\chi^2 = 17.17$	$\chi^2 = 10.83$	F = 1.81
Prob > Stat	0.0042	0.0549	<0.001
Error Structure	Random Effects GLS	RE + Driscoll–Kraay	Dynamic CCEMG

The constant terms in the Random Effects models are 1.5035 ($p = 0.517$) and 1.5197 ($p = 0.538$) and are statistically insignificant. Model diagnostics show R-squared values of 0.0376 for both Random Effects models and 0.14 for the Mean Group specification, indicating modest explanatory power across estimators. The Wald statistics ($\chi^2 = 17.17$ and $\chi^2 = 10.83$) with probability values 0.0042 and 0.0549, respectively, and the F-statistic of 1.81 ($p < 0.001$) for the CCEMG model confirm overall model significance. These estimations account for different error structures, including Random Effects GLS, Random Effects with Driscoll–Kraay corrections, and Dynamic CCEMG, thereby addressing potential issues of heteroskedasticity, autocorrelation, cross-sectional dependence, and slope heterogeneity.

DISCUSSION

The robustness analysis of the determinants of account ownership reveals several important dynamics regarding the role of digital finance, financial sector stability, and

macroeconomic conditions in promoting financial inclusion. The results obtained from multiple estimation techniques confirm that the key relationships remain broadly consistent across alternative model specifications, indicating that the findings are stable and reliable.

Theoretical Implications of Digital Lending Effects

The positive and significant relationship between digital lending (ΔVMMTPG) and account ownership across static estimators confirms the core proposition of financial intermediation theory (Boitan, 2016; Danisman & Tarazi, 2020). Digital lending platforms effectively reduce transaction costs and overcome informational frictions that have historically excluded low-income populations from formal financial systems. This finding empirically validates the argument that technology-enabled intermediation expands the frontier of financial inclusion in emerging economies.

However, the weakening of this effect in the Dynamic CCEMG estimator ($\beta = 3.842$, $p = 0.785$) suggests that institutional and cross-country heterogeneity significantly moderates the digital lending-inclusion nexus. This aligns with Gabor and Brooks (2019), who caution that digital financial inclusion is not universally beneficial and depends on regulatory frameworks, consumer protection mechanisms, and technological readiness. The findings imply that while digital lending *can* promote inclusion, the magnitude of its impact varies considerably across African economies depending on local institutional conditions. This heterogeneity may reflect differences in the quality of digital infrastructure, the sophistication of financial regulatory environments, the prevalence of fraud, and the level of digital literacy among populations.

Credit Risk as a Binding Constraint

The consistently negative and statistically significant effect of non-performing loans (ΔNPL) on account ownership across all specifications provides strong empirical support for credit risk theory in the context of digital finance. Higher NPL ratios indicate deteriorating asset quality, which weakens financial institutions' capacity to extend new credit and absorb new customers (Musau et al., 2018; Ozili, 2018). When banks and fintech lenders face rising defaults, they become more risk-averse, tighten lending standards, and reduce their outreach to previously underserved segments, thereby constraining financial inclusion.

Importantly, the coefficient magnitude in the Dynamic CCEMG model (-1.2096, $p = 0.004$) is substantially larger than in static models (-0.73), suggesting that the constraining effect of credit risk on financial inclusion is amplified when cross-country dependencies and dynamic adjustments are considered. This implies that financial instability in one country can have spillover effects on financial inclusion outcomes in neighbouring economies through regional financial linkages, cross-border banking activities, or investor sentiment. For instance, a banking crisis in a large economy like Nigeria or South Africa could reduce risk appetite among financial institutions operating across the region, leading to a general contraction in credit access.

This finding reinforces the policy recommendation that digital lending expansion must be accompanied by prudent credit risk management frameworks, including robust borrower assessment mechanisms, early warning systems, and regulatory oversight of fintech lending platforms (Sommer, 2021; Ahmed et al., 2024). Without such safeguards, the rapid expansion of digital credit may paradoxically undermine the very goal of inclusive finance by creating a cycle of defaults, deleveraging, and reduced access.

The Role of Digital Infrastructure

Mobile cellular subscription (LNMCS) exhibits a positive but statistically insignificant effect in static models, but becomes significant ($\beta = 0.1208$, $p = 0.017$) in the Dynamic CCEMG estimator. This pattern suggests that digital infrastructure alone does not guarantee financial inclusion; rather, its effect is conditional on broader technological spillovers and cross-country interconnectedness.

From the perspective of the Technology Acceptance Model (TAM) (Miftari et al., 2024; Kampani, 2024), mobile infrastructure provides the *enabling platform* for digital financial services, but users' perceived usefulness and ease of use are equally important determinants of adoption. The significant effect in the CCEMG model may reflect network effects and technology diffusion spillovers across countries, where improvements in one economy's digital connectivity facilitate adoption in neighbouring economies through demonstration effects, cross-border digital commerce, and regional integration of payment systems. For example, the success of M-Pesa in Kenya has inspired similar mobile money platforms across East Africa, creating regional momentum that accelerates adoption.

This finding supports Nkechika (2022) and Ravikumar and Ranganath (2025), who emphasize that mobile technology is a necessary but not sufficient condition for digital financial inclusion. Investments in digital literacy, consumer trust, user-friendly interfaces, and affordable data plans are complementary requirements for translating infrastructure improvements into tangible inclusion outcomes. Without these complementary investments, the presence of mobile networks may not translate into increased account ownership, particularly among rural and low-literacy populations.

Macroeconomic Dynamics

The macroeconomic variables reveal relatively weak and mixed effects on account ownership. Economic growth generally displays a positive relationship with financial inclusion, suggesting that expanding economic activity can increase income levels and stimulate participation in the formal financial sector. However, the influence is not consistently strong across all estimators, indicating that economic growth alone may not be sufficient to expand financial inclusion without complementary financial sector development. This observation is consistent with Nguema and Lera (2025) and Kattan-Rodríguez and Galindo-Manrique (2025), who emphasize that the benefits of economic growth for financial inclusion depend on the depth and accessibility of financial systems. In countries where financial systems are underdeveloped, even robust economic growth may fail to translate into increased account ownership if banks are concentrated in urban areas or if entry barriers remain high.

In contrast, inflation shows a negligible and statistically insignificant effect on account ownership, suggesting that price level fluctuations do not directly influence individuals' decisions to hold financial accounts within the observed sample. This result aligns with the argument of Ozili (2018) that institutional, technological, and financial sector factors tend to play a more dominant role in shaping financial inclusion outcomes than short-term macroeconomic price movements. Inflation may affect the real value of savings, but for unbanked populations who primarily transact in cash, the direct link between inflation and the decision to open a formal account remains weak. The significant cross-sectional dependence found in the CD test (Table 8) suggests that common shocks, such as commodity price cycles, global financial conditions, or regional economic integration, affect financial inclusion dynamics across countries

simultaneously. This justifies the use of robust estimation techniques that account for such interdependence.

Policy Implications

The findings of this research have several important policy implications for African economies seeking to leverage digital financial services for inclusive growth:

1. **Prioritize digital financial infrastructure.** The positive effect of mobile money transactions on account ownership underscores the need for continued investment in digital payment systems, interoperable platforms, and last-mile connectivity to reach underserved populations. Governments should incentivize fintech innovation through regulatory sandboxes and supportive policies while ensuring that digital payment systems are affordable and accessible to low-income users.
2. **Strengthen credit risk governance.** The consistently negative effect of non-performing loans on inclusion suggests that digital lending expansion must be accompanied by robust risk management frameworks. Regulatory authorities should implement: (a) borrower protection mechanisms to prevent over-indebtedness, including caps on interest rates and transparent disclosure requirements; (b) standardized credit reporting systems to improve information sharing and reduce asymmetric information; (c) prudential oversight of fintech lenders, including capital adequacy requirements and stress testing; and (d) early warning systems to detect systemic risk accumulation in the digital lending sector.
3. **Enhance technological infrastructure.** The positive effect of mobile subscriptions on inclusion (particularly when cross-country dependence is considered) indicates the importance of improving telecommunications infrastructure, especially in rural and remote areas. Governments should incentivize network expansion through public-private partnerships, reduce spectrum costs, ensure affordable data access, and promote digital literacy programs to maximize the benefits of connectivity.
4. **Promote financial literacy and consumer protection.** Given that infrastructure alone is insufficient, complementary investments in financial education, digital literacy, and consumer awareness are essential to translate access into meaningful usage and welfare improvements. Financial literacy programs should target vulnerable groups, including women, rural populations, and youth, to build trust and competence in using digital financial services.

5. Adopt regionally coordinated approaches. The significant cross-sectional dependence identified in this research suggests that financial inclusion policies should consider regional spillovers and common shocks. Regional coordination on regulatory standards, data sharing, and crisis response mechanisms could enhance the effectiveness of national policies. African regional bodies such as the African Union and regional economic communities should facilitate harmonized fintech regulations to reduce regulatory arbitrage and promote cross-border digital finance.
6. Balance innovation with stability. The finding that credit risk constrains inclusion highlights the delicate balance between promoting innovation and maintaining financial stability. Policy makers should adopt a proportionate regulatory approach that encourages responsible innovation while protecting consumers and safeguarding the financial system. This includes implementing graduated regulatory requirements based on the scale and systemic importance of digital lenders, ensuring that small fintechs are not overburdened while larger platforms are adequately supervised.

Limitations And Future Research Directions

While this research provides robust empirical evidence on the determinants of financial inclusion in African economies, several limitations should be acknowledged.

Proxy Limitations: First, the proxy variables used to operationalize key constructs have inherent limitations. The value of mobile money transactions (VMMTPG) captures the volume of digital financial activity but does not distinguish between different types of digital lending (e.g., peer-to-peer lending, bank-led digital credit, fintech microloans, or buy-now-pay-later schemes). Similarly, account ownership as a measure of financial inclusion captures only the extensive margin of inclusion (access) and does not reflect the intensive margin (usage intensity, quality of services, transaction frequency, or consumer welfare). Future research could employ more nuanced measures of financial inclusion, such as the Financial Inclusion Index or composite indicators that capture usage, quality, and welfare dimensions.

Low Explanatory Power: Second, the relatively low R-squared values (ranging from 0.037 to 0.14) indicate that the selected explanatory variables explain only a modest portion of variation in account ownership. This suggests that other important determinants of financial inclusion—such as financial literacy, trust in financial

institutions, cultural attitudes toward banking, gender disparities, rural-urban divides, regulatory quality, political stability, and institutional trust—are not fully captured in the current model. Future research should incorporate these additional dimensions to improve model explanatory power and provide a more complete understanding of the drivers of financial inclusion.

Macro-Level Perspective: Third, the research adopts a macro-level, cross-country perspective that may obscure within-country heterogeneity. African countries are characterized by substantial regional, urban-rural, and demographic variations in financial inclusion outcomes. For instance, account ownership rates in urban areas are typically much higher than in rural areas, and gender gaps in financial inclusion remain persistent across many countries. Future studies using household-level survey data (e.g., World Bank Findex data, national household surveys, or Demographic and Health Surveys) could provide more granular insights into the mechanisms through which digital lending and credit risk affect different population segments, particularly women, youth, and rural dwellers.

Causal Complexity: Fourth, the study treats digital lending and credit risk as separate constructs, but the relationship between them is likely more complex and potentially bidirectional. Digital lending platforms may influence credit risk through improved information sharing and alternative data usage, while credit risk may, in turn, influence the adoption and design of digital lending products. Higher credit risk may lead platforms to tighten lending criteria, reducing access for marginal borrowers, while easier access to credit may increase default rates among less creditworthy borrowers. Future research employing structural equation modelling (SEM), instrumental variable approaches, or panel vector autoregression (PVAR) could better identify the causal pathways and potential feedback loops among these variables.

Temporal Scope: Fifth, the temporal scope of the analysis (2005–2024) covers a period of rapid technological change and includes the COVID-19 pandemic, which may have introduced structural breaks in the data. The pandemic accelerated digital financial adoption in many countries, potentially altering the baseline relationships. Future research could examine whether the relationships identified in this study have strengthened or weakened in the post-pandemic era, and whether the acceleration of digital financial services during the pandemic has produced lasting changes in financial

inclusion patterns. A pre-COVID (2005–2019) versus post-COVID (2020–2024) comparative analysis could be particularly illuminating.

Regional Comparative Studies: Finally, while this research focuses on African economies, comparative studies with other emerging regions (South Asia, Latin America, Southeast Asia) could help identify whether the determinants of financial inclusion are region-specific or globally generalizable. Such comparative analysis could inform more targeted policy interventions tailored to the unique characteristics of different regional contexts, and could also identify best practices that could be transferred across regions.

Future Research Directions: Building on these limitations, future research could pursue the following avenues: (a) conduct sub-regional analyses to examine whether the determinants of financial inclusion differ across West, East, Southern, Central, and North Africa; (b) employ gender-disaggregated data to examine whether digital lending has differential effects on female versus male financial inclusion; (c) undertake qualitative case studies in countries with successful digital lending ecosystems (e.g., Kenya, Nigeria, Tanzania, Ghana) to understand the institutional and behavioral factors underlying success; (d) test for non-linear relationships, including threshold effects, to determine whether there is an optimal level of digital lending intensity beyond which inclusion benefits diminish or credit risk becomes excessive; and (e) integrate household-level surveys with aggregate data to provide a more complete understanding of the mechanisms linking digital finance to welfare outcomes.

CONCLUSION

This research examined the determinants of financial inclusion across 44 African economies from 2005 to 2024, focusing on digital lending, credit risk, digital infrastructure, and macroeconomic conditions. The empirical findings confirm that digital lending (mobile money transactions) significantly promotes account ownership across static estimators ($\beta = 0.114\text{--}0.125$, $p < 0.05$), though this effect weakens when cross-country heterogeneity is considered, while credit risk (non-performing loans) consistently and negatively constrains inclusion across all specifications ($\beta = -0.731$ to -1.210 , $p < 0.05$), demonstrating that financial instability undermines inclusive finance. Mobile communication infrastructure shows a positive effect that becomes significant only when cross-country dependence is accounted for ($\beta = 0.121$, $p < 0.05$), suggesting regional spillovers and network effects, whereas macroeconomic variables (GDP growth

and inflation) exhibit limited and inconsistent influence. These findings collectively confirm that financial inclusion is not merely an access outcome but a conditional process whose sustainability depends on effective credit risk governance, robust digital infrastructure, and supportive institutional environments, with heterogeneity across African economies moderating the digital lending-inclusion nexus.

The theoretical contribution lies in integrating financial intermediation theory, credit risk theory, and the Technology Acceptance Model within a unified empirical framework applied to African economies, while methodological rigor is demonstrated through multiple robust estimators (FE with Driscoll–Kraay, PCSE, PCSE with AR(1), RE, and Dynamic CCEMG) that account for cross-sectional dependence, slope heterogeneity, and dynamic adjustments. Policy implications emphasize strengthening digital financial ecosystems, enhancing technological infrastructure, ensuring prudent credit risk management, and adopting regionally coordinated regulatory approaches to sustain inclusive financial development. However, the modest explanatory power ($R^2 = 0.037\text{--}0.14$) reveals important limitations, suggesting future research should incorporate additional determinants such as financial literacy, trust in institutions, gender disparities, regulatory quality, and household-level behavioural factors, while comparative studies across emerging regions and sub-regional analyses within Africa would further enrich understanding of contextual factors shaping digital financial inclusion and its welfare implications.

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