DIGITAL FINANCIAL INCLUSION AND POVERTY REDUCTION IN SUB-SAHARAN AFRICA: DYNAMIC PANEL EVIDENCE

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Abstract

This study examined the influence of digital financial inclusion on poverty reduction in Sub-Saharan Africa. The study covers the period 2005-2024 across 31 Sub-Saharan African countries. The study uses households' and Non-Profit Institutions Serving Households' final consumption expenditure as a proxy for poverty reduction, and measures digital financial inclusion through mobile money account ownership among adults aged 15 years and above. The study uses fixed effects, Dynamic Common Correlated Effects, Pooled Mean Group, and CS-ARDL estimations. The findings are: the fixed-effects estimate shows a positive and statistically significant DFI coefficient (β = 6.968, p < .01), while the DCCE coefficient is also positive and significant (β = 2.642, p < .05). The PMG results reveal no significant immediate effect (β = -2.1805, p = .2695) but a positive and significant long-run coefficient (β = 17.7075, p = .021). In contrast, the CS-ARDL current and lagged DFI coefficients are positive but statistically insignificant. Thus, the findings are mixed and model-dependent: the fixed-effects, DCCE, and PMG long-run specifications indicate a positive association, whereas the PMG short-run and CS-ARDL estimates provide no statistically significant evidence for DFI. Digital financial inclusion supports poverty reduction in Sub-Saharan Africa mainly over time, though effects vary across models. Policymakers should promote affordable, reliable, actively used digital services alongside financial literacy initiatives.

Keywords: Digital Financial Inclusion; Mobile Money; Poverty Reduction; Sub-Saharan Africa; Financial Intermediation

1. Introduction

Poverty remains one of the most persistent development problems in Sub-Saharan Africa (SSA), despite decades of economic reform, financial sector expansion and technological change. The problem is more than low income. It is also characterised by weak consumption capacity, low resilience to shocks, limited access to health and education, insecure livelihoods, and exclusion from productive opportunities (World Bank, 2022; Kumar & Qin, 2023; Omenihu et al., 2024). This multidimensional character matters because it shifts the focus from the mere existence of financial services to the extent to which households can use them to stabilise consumption, mobilise savings, receive transfers, finance livelihoods, and manage risk. Thus, the expansion of digital finance has become central to the debate about poverty reduction in developing economies. In particular, in SSA, mobile money, point-of-sale channels, agent networks and other technology-enabled services have emerged partly in response to the limited reach of conventional branch-based banking (Tay et al., 2022; Osuma, 2025).

The poverty-reducing strategy of digital financial inclusion (DFI) is intuitively strong, but empirically more complex. Distance, documentation requirements, collateral constraints, minimum balances and the direct and indirect costs of visiting financial institutions exclude many low-income households from traditional banking. Digital platforms can help to overcome some of these barriers by providing small-value payments, transfers, savings and, in some cases, credit via mobile phones and agent networks (Anakpo et al., 2023; Udo & Akpan, 2026). However, access is not equal to effective inclusion. High transaction charges, transaction failures, lack of digital proficiency, agents with insufficient liquidity, or a rare use of a mobile money account can also be reasons for low usage of a household's mobile money account. This distinction matters because it is the activities that users can undertake with the service, not just whether they have opened an account (Omenihu et al., 2024; Adefabi, 2025) that determine the welfare effect of digital finance.

Thus, the evidence is positive but inconsistent. Studies in developing countries generally associate financial inclusion with lower poverty and inequality (Omar & Inaba, 2020; Kumar & Qin, 2023), while studies on digital finance identify channels through which technology can reduce vulnerability, ease credit constraints and support consumption or entrepreneurship (Wang & He, 2020; Ouyang et al., 2022; Liu & Guo, 2023). Evidence from Africa is also increasingly supportive. Iwedi et al. (2024) link mobile money, point-of-sale infrastructure and mobile payments to higher consumption expenditure in Rivers State. Udo and Akpan (2026) report that active use of digital services is a particularly important predictor of poverty reduction in rural South-South Nigeria. Osuma (2025) also finds that digital financial services can be more effective than conventional access indicators in expanding inclusion across SSA. However, Simon-Ilogho and Moloi

(2026) find that mobile money and ATM availability do not significantly alleviate poverty in their SSA panel. Saka et al. (2025) also show that financial inclusion in Ghana is more evident through indirect human-development pathways than through a direct reduction in household poverty. These differences caution against viewing DFI as an automatic anti-poverty technology.

A second unresolved issue is timing. Much of the policy discussion presumes that digital access should quickly translate into better welfare because transactions become cheaper and more convenient. In reality, the benefits might be cumulative. New users must learn the technology, establish trust, build transaction history, learn about relevant products, and integrate digital channels into their household or business routines. Credit constraints may ease only after repeated use, and savings or enterprise effects may take several periods to manifest in consumption outcomes. This temporal distinction is especially relevant in SSA where disparities in infrastructure, income and financial literacy across countries are stark. Thus, a regression taken at one point in time may underestimate a gradual mechanism, whereas a model that considers only the long run may obscure weak or even disruptive short-run adjustment. Because poverty is multidimensional, the empirical outcome used in this study does not represent poverty reduction in its full sense. It captures the consumption dimension of material welfare through Households and NPISH final consumption expenditure and is therefore interpreted as a consumption-based welfare proxy relevant to poverty-reduction analysis. To address the timing question, the study analyses the short- and long-run relationship between DFI and this welfare proxy in SSA. It uses 31 countries and 620 country-year observations and employs fixed-effects, Dynamic Common Correlated Effects (DCCE), and Pooled Mean Group (PMG) estimators. The study makes three contributions. First, it explicitly focuses on digital financial participation through mobile money account ownership, rather than equating broad financial development with inclusion. Second, it contrasts short-run and long-run estimates to test whether the association between DFI and the welfare proxy differs over time. Third, it blends positive findings with contradicting evidence from Africa, thus avoiding the assumption that digitalisation necessarily extends to the poorest households. The study therefore tests the theoretical expectation that any welfare association may emerge gradually rather than assuming an accumulated effect before estimation. It hypothesises that digital financial inclusion is positively associated with the consumption-based welfare outcome in SSA, while leaving open the possibility that the short-run association is weak or statistically indistinguishable from zero.

2. Literature Review and Theoretical Framework

Digital financial inclusion and the poverty-reduction mechanism

Digital financial inclusion is the use of formal financial services via technology-enabled channels such as mobile money, digital payments, fintech platforms, internet banking, digital wallets, point-of-sale terminals and agent networks (Anakpo et al., 2023; Tay et al., 2022). Its evolution has moved beyond physical branches to include conventional financial inclusion. Savings, credit and risk management through traditional inclusion may benefit welfare but branch-based systems are often expensive or inaccessible for rural and low-income users (Omar & Inaba, 2020; Kumar & Qin, 2023). Digital channels can change this cost structure by removing the need for travel, enabling small-value transactions, and allowing transfers outside normal banking hours. The relevant development question, however, is not whether technology increases access in the abstract, but whether the financial participation it engenders changes the resources and choices available to poor households.

Four transmission channels are especially important. First, credit and production. Poor households and microenterprises often face constraints on collateral, information, and documentation in formal credit markets. Digital transaction records and platform-based services can reduce these barriers and facilitate working-capital finance, enterprise investment, or livelihood diversification (Anakpo et al., 2023; Ouyang et al., 2022). Ouyang et al. (2022), for example, link digital financial inclusion to reduced rural relative poverty through higher wage income, fewer credit constraints, and entrepreneurship. This route is economically feasible, but it is not universally benign. Digital credit can also increase vulnerability if loans are expensive, frequently rolled over or used mainly for consumption rather than productive investment. So, digital credit itself will not reduce poverty, the terms, purposes and repayment implications of borrowing are still critical.

The second channel is savings, payments and consumption smoothing. Digital accounts could make it easier to hold small balances, receive transfers, pay for goods and move resources between locations. For households with volatile earnings and low income, income timing may matter as much as its amount. Faster and safer transfers can reduce the need to sell assets or defer necessary consumption in the face of shocks. Iwedi et al. (2024) found a positive relationship between mobile money accounts, POS availability, mobile payments, and consumption expenditure in Rivers State. Liu and Guo (2023) also found that digital financial inclusion could reduce vulnerability to relative poverty through income distribution, household health, and development-oriented consumption. These results suggest a broader welfare channel than credit: digital finance

can matter by improving liquidity management and the reliability of everyday transactions.

The third channel is risk sharing and resilience. Poverty is dynamic, and households can fall into poverty due to illness, crop loss, unemployment, insecurity or sudden family obligations. Mobile transfers can extend the effective support network beyond the immediate locality, and digital savings can help create small buffers against emergencies. Wang and He (2020) find that digital financial services reduce farmers' vulnerability to poverty in rural China mainly by improving risk-coping capacity. Earlier mobile-money evidence from East Africa also emphasises the need for lower transfer costs and better risk sharing (Jack & Suri, 2014; Riley, 2018). The relevance for SSA is significant, but the transferability of specific results depends on the network reach, the agent density and the maturity of the surrounding digital ecosystem.

The fourth channel is to reduce transaction costs and market participation. Digital payments can reduce transport, waiting and information costs. Digital payments can benefit informal traders or farmers by facilitating payments and linking them to wider markets. Osuma (2025) reveals that digital financial services are more effective than ATM availability in promoting financial inclusion over parts of SSA. Thus, mobile channels may be more adapted to environments with sparse branch infrastructure. But cost reduction is not automatic. High cash-out fees, poor network reliability or few agents can shift them rather than eliminating transaction costs. Eje (2022) found that different financial channels in Nigeria have different poverty effects, and Anakpo et al. (2023) identified infrastructure, online literacy, cyber risk, and consumer-protection gaps as persistent constraints.

Empirical evidence: positive effects, conditional effects and contradictions

Cross-country evidence provides a broad basis for the claim that financial inclusion can reduce poverty, but it also points to important conditions. Omar and Inaba (2020) find that financial inclusion reduces poverty and income inequality using a multidimensional financial inclusion index and a large panel of developing countries. Kumar and Qin (2023) extend this logic, showing that the effect is stronger when women and poor households have better access and when institutional quality and education are more supportive. These studies matter because they reject a purely supply-side reading of inclusion. However, they measure financial inclusion more broadly than mobile money or digital usage and thus cannot identify whether technology-enabled channels have a separate welfare effect.

Several studies have examined digital finance more directly, with generally favourable findings. Digital financial services reduce rural Chinese households' vulnerability to poverty (Wang & He, 2020). Ouyang et al. (2022) find lower rural relative poverty through wage, credit and entrepreneurship mechanisms, while Liu and Guo (2023) find effects through inequality, health and development-oriented consumption. Using system GMM, Xie (2023) also finds that digital inclusive finance contributes to regional poverty reduction in China. The studies provide fairly strong evidence that digital finance can affect welfare. However, the institutional and technological settings differ substantially from those in much of SSA. China has deep platform integration, extensive digital infrastructure and a dense e-commerce network. Thus, the positive mechanism is informative, but its magnitude cannot be directly transferred to African contexts.

African and Nigerian studies bring the analysis closer to this paper's setting. Adefabi (2025) shows that digital finance access and frequency of use increase the probability of improved poverty-reduction outcomes, while perceived barriers reduce such gains. Similarly, Udo and Akpan (2026) discovered that usage is the strongest predictor of poverty reduction in rural South-South Nigeria, followed by access, quality, reliability and affordability. Hussaini and Dikko (2025) find positive relationships between several digital channels and welfare in North-Western Nigeria. At the regional level, Osuma (2025) shows the increasing importance of digital financial services relative to ATM-based measures of inclusion. Together, these studies support a key distinction for this paper: active, reliable use appears more important than the mere presence of digital infrastructure.

The counterevidence is important because it defines the limits of the optimistic story. Simon-Ilogho and Moloi (2026), in their analysis for SSA, find that the availability of ATM and the use of mobile money are not significantly helping in the reduction of poverty, although mobile subscriptions have relevance to poverty reduction. Saka et al. (2025) show that financial inclusion in Ghana does not directly affect household poverty or consumption but affects it indirectly through education, health, and income equality. Eje (2022) finds positive effects for some Nigerian channels of inclusion and negative effects for others. These results imply that differences in measurement, intensity of use, literacy, infrastructure and the welfare outcome chosen can materially change the conclusion. They also argue that account ownership or platform availability may be necessary but not sufficient for poverty reduction.

Another question is whether DFI has an immediate or delayed effect. Learning, entrepreneurship, savings accumulation, transaction histories, risk management. Many studies find mechanisms that are inherently dynamic. Much of the literature, however, tests average relationships without explicitly distinguishing short-run adjustment from long-run equilibrium. Mashoene and Schaling (2026) partially address this problem by showing that inclusive

growth is supported by digital financial inclusion, which then contributes to poverty reduction. Their finding suggests that DFI may operate through broader structural changes rather than through an immediate household response. This paper directly builds on this insight by comparing short- and long-run coefficients for DFI in the same SSA framework.

Financial Intermediation Theory

The Financial Intermediation Theory was applied, which suggests that intermediaries can enhance resource allocation by linking savers with borrowers and by reducing information asymmetry, transaction costs, and liquidity constraints. The present study views mobile money platforms and related digital services as modern intermediation channels. They reduce the costs of transferring and storing funds and can link households previously unable to access formal finance to broader financial networks. Thus, the theory provides a plausible link between DFI and consumption stability, enterprise activity and poverty reduction (Omar & Inaba, 2020; Tay et al., 2022).

The theory is useful, but limited in low-income digital settings. It assumes that once barriers to intermediation are lowered, users can turn access into efficient economic decisions. In practice, low income, weak digital skills, unreliable infrastructure, and limited product quality can prevent formal access from translating into productive use (Tay et al., 2022; Anakpo et al., 2023). Empirically, the coefficient on DFI should not be interpreted as a technological effect independent of user capability. A positive coefficient is more reasonably interpreted as the average welfare association of entry into a digital financial network conditional on country conditions. The theory also supports the paper's dynamic expectation that intermediation benefits can compound as users trust, learn to use services and repeatedly mobilise savings or transfers.

The hypothesis is therefore expressed in terms of welfare since the dependent variable is household final consumption expenditure: H1: Digital financial inclusion has a positive and statistically significant association with the consumption-based welfare outcome used as a proxy for poverty reduction in Sub-Saharan Africa. The dynamic specification allows the data to indicate whether this association is contemporaneous or primarily long-run.

3. Methodology

The study adopts an ex post facto panel design using secondary data for 31 Sub-Saharan African countries over a 20-year period (2005-2024). The study uses 620 country-year observations, or 20 per country, in a balanced panel. The country set includes Benin, Burkina Faso, Cabo Verde, Côte d'Ivoire, Ghana, Mali, Mauritania, Niger, Nigeria, Senegal, Sierra Leone, Togo, Comoros, Kenya, Madagascar, Mauritius, Mozambique, Rwanda, Seychelles, Tanzania, Angola, Cameroon, Central African Republic, Chad, Democratic Republic of the Congo, Republic of the Congo, Botswana, Eswatini, Lesotho, Namibia and South Africa. The data are drawn from the global sources cited in the thesis, especially the World Development Indicators, Global Findex, and Worldwide Governance Indicators.

The poverty reduction (consumption-based welfare outcome) (POV) is measured by final consumption expenditure of Households and Non-Profit Institutions Serving Households in current US dollars. It is not a direct measure of poverty reduction or poverty headcount; rather, it captures nominal household consumption capacity and is interpreted as a material-welfare proxy relevant to poverty-reduction analysis. This choice is closely linked to consumption smoothing, one channel through which digital finance could matter. Because current-US-dollar values are affected by inflation and exchange-rate movements, interpret cross-country and intertemporal coefficients cautiously as nominal welfare associations; where the data permit, examine a constant-price and preferably PPP-adjusted consumption measure as a robustness check. The main explanatory variable, DFI, is adult mobile money account ownership (aged 15 and above). The annual estimation series was constructed from Global Findex observations. This measure captures access or account ownership rather than effective use: it does not observe transaction frequency, balance size, service quality, savings activity, credit use, or the productive purpose of transactions. Accordingly, the DFI coefficient reflects an association with mobile-money account ownership, not the effect of active digital financial use.

The models control for GDP per capita (GDPPC), trade openness (TOP), education (EDU) and financial development (FD), as these variables may independently influence welfare and may also be related to digital financial expansion. EDU is described as a WDI school-enrollment or related education indicator, while FD is described as a WDI/IMF indicator of financial-system depth or efficiency. The empirical strategy is intentionally staggered. First, fixed-effects estimation is used to examine within-country associations while controlling for unobserved, time-invariant country characteristics. This matters because SSA countries differ in geography, historical institutions, financial-system structure and other persistent characteristics that may be related to DFI. The reported baseline fixed-effects results therefore control for country-specific time-invariant heterogeneity. Although the thesis empirical-model notation includes time effects, the reported fixed-effects regression output does not separately verify the inclusion of year dummies; this paper therefore does not claim year fixed effects without confirmation from the estimation output. The Hausman specification test strongly rejected the random-effects model ($\chi^2 = 56.188$, $p < .001$),

supporting fixed effects for the baseline interpretation.

Second, the study reports a Dynamic Common Correlated Effects (DCCE) model. DCCE is relevant because countries may be affected by unobserved common factors and shared shocks, while the relationship between digital finance and welfare may also be dynamic (Chudik & Pesaran, 2015). The thesis specifies DCCE in general form using cross-sectional averages to capture common factors, but it does not report the exact cross-sectional-average variables, their lag order, the dynamic lag order or whether slopes were estimated heterogeneously across countries. Those details are therefore not invented here and should be verified from the original estimation command or output for full replication. Third, the Pooled Mean Group (PMG) model separates short-run changes from long-run coefficients by allowing short-run coefficients, adjustment speeds and error variances to differ across countries while imposing homogeneous long-run coefficients. The thesis does not report a PMG-versus-Mean-Group Hausman comparison; consequently, the long-run homogeneity restriction remains an untested modelling assumption and is treated as a limitation. The PMG error-correction term indicates whether deviations from the estimated long-run relationship are systematically corrected over time. Because digital financial inclusion and welfare may be jointly determined, coefficients are interpreted as associations rather than strict causal effects. Dynamic lags improve temporal specification but do not, by themselves, eliminate reverse causality or omitted-variable endogeneity. Diagnostic analysis includes variance-inflation factors, likelihood-ratio heteroskedasticity testing, the Wooldridge test for first-order autocorrelation, Fisher-type ADF and PP panel unit-root tests, and Pedroni, Kao and Westerlund cointegration tests. The thesis also reports a Pesaran cross-sectional-dependence test for the moderation specification (CD = 0.575, p = 0.5656; average absolute off-diagonal correlation = 0.460), which fails to reject cross-sectional independence at the 5% level. Because that test is reported for the moderation specification rather than the baseline equation, DCCE and CS-ARDL are retained principally as robustness estimators against potential common-factor dependence rather than on the claim that baseline cross-sectional dependence has been established.

Table 1. Variables and measurement

Variable	Abbrev.	Measurement	Source	
Consumption-based welfare proxy	POV	Households and NPISHs final consumption expenditure (current US$); used as a nominal consumption-based welfare proxy, not a direct poverty measure	World Indicators	Development
Digital financial inclusion	DFI	Mobile money account ownership among adults aged 15 years and above; access/ownership measure rather than active use	Global Findex	
GDP per capita	GDPPC	GDP per capita (constant 2015 US$)	World Indicators	Development
Trade openness	TOP	Exports plus imports as a percentage of GDP	World Indicators	Development
Education	EDU	School enrollment, secondary (% gross)	World Indicators	Development
Financial development	FD	Domestic credit to private sector (% of GDP)	World Indicators	Development

4. Data Presentation and Analysis of Results

Table 2. Descriptive Statistics

Variable	Count	Mean	SD	Minimum	Maximum
POV	620	1564.871	2041.127	0	13789.27
DFI	620	12.68	18.85571	0	93.57576

IQ	620	-0.4955651	0.6275785	-1.64552	0.886108
GDPPC	620	2445.242	3089.625	349.8212	19481.65
TOP	620	69.94058	37.39599	0	222.1783
EDU	620	33.01993	31.41227	0	112.3112
FD	620	20.43962	25.54291	0	142.422

Source: Analysis Report (2026).

Table 2 presents the descriptive statistics for the consumption-based welfare proxy (POV), digital financial inclusion (DFI), institutional quality (IQ), GDP per capita (GDPPC), trade openness (TOP), education (EDU) and financial development (FD). All variables have 620 observations. The observations cover 20 years in 31 Sub-Saharan African countries. The mean of POV is 1,564.871 with a standard deviation of 2,041.127, suggesting large variation in household consumption welfare across the panel. DFI: 12.68 (average), 18.85571 (standard deviation), 0 (minimum), 93.57576 (maximum). The low mean and wide range indicate high inequality in digital financial participation across the countries and periods studied.

Table 3. Correlation Matrix

Variables	**POV**	**DFI**	**IQ**	**GDPPC**	**TOP**	**EDU**	**FD**
POV	1.000						
DFI	0.747 (0.000)	1.000					
IQ	0.591 (0.000)	0.632 (0.000)	1.000				
GDPPC	0.969 (0.000)	0.765 (0.000)	0.620 (0.000)	1.000			
TOP	0.646 (0.000)	0.494 (0.000)	0.445 (0.000)	0.659 (0.000)	1.000		
EDU	0.547 (0.000)	0.618 (0.000)	0.577 (0.000)	0.533 (0.000)	0.310 (0.000)	1.000	
FD	0.423 (0.000)	0.615 (0.000)	0.549 (0.000)	0.417 (0.000)	0.184 (0.000)	0.524 (0.000)	1.000

Source: Analysis Report (2026)

Table 3 and 4 show that DFI is positively and significantly associated with POV (r = 0.747, p = 0.000). IQ, GDPPC, TOP, EDU and FD are also positively correlated with POV. GDPPC shows the strongest bivariate association with POV (r = 0.969), which warrants particular caution because the dependent variable and GDP per capita may capture closely related dimensions of aggregate economic welfare.

Table 4. Variance Inflation Factor

Variable	VIF	1/VIF
DFI	3.470	0.288
IQ	3.430	0.292
GDPPC	2.130	0.469
TOP	1.900	0.527
EDU	1.850	0.540
FD	1.840	0.544
Average	2.440	

Source: Analysis Report (2026)

The variance inflation factors reported in Table 4 range from 1.840 to 3.470, with an average of 2.440. These values do not indicate severe linear collinearity among the regressors under conventional VIF thresholds, but they do not resolve the interpretation or identification concern created by the exceptionally high POV-GDPPC correlation.

Table 5a. Baseline Panel Diagnostic Tests

Diagnostic	Statistic	df	p-value	Decision at 5%
Likelihood-ratio heteroskedasticity test	LR χ^2 = 1479.18	30	0.0000	Reject homoskedasticity
Wooldridge first-order autocorrelation test	F = 3.062	F(1,30)	0.0904	Fail to reject no AR(1)

Source: Analysis Report (2026).

Table 5b. Baseline Panel Diagnostic Tests

Model	Test Used	Test Statistic	p-value	Average Absolute Off-Diagonal Correlation	Decision at 5%
Moderation model: POV, DFI, IQ, DFI_IQ, EDU and FD	Pesaran CD test	0.575	0.5656	0.460	Fail to reject H_0

Source: Analysis Report (2026).

In Table 5a and 5b, the baseline model fails the homoskedasticity assumption. The likelihood-ratio heteroskedasticity test produces an LR chi-square statistic of 1479.18 with a p-value of 0.0000, so the null of constant error variance is rejected. The Wooldridge test produces F(1,30) = 3.062 with p = 0.0904. Accordingly, there is no strong evidence of first-order autocorrelation at the 5 per cent level, although the result provides weak evidence at the 10 per cent level. These findings justify using estimation and inference procedures robust to panel error-structure problems. Cross-sectional dependence was assessed using the Pesaran CD test. The test produced a CD statistic of 0.575 with a p-value of 0.5656. Since the p-value exceeds the 5% significance level, the null hypothesis of cross-sectional independence is not rejected, indicating no statistically significant evidence of residual cross-sectional dependence. However, the average absolute off-diagonal correlation of 0.460 indicates a moderate degree of pairwise association across countries. Consequently, the DCCE and CS-ARDL estimators are interpreted primarily as robustness estimators that accommodate possible common shocks and unobserved cross-country factors, rather than as responses to statistically established cross-sectional dependence.

Table 6. Fisher-Type Panel Unit Root Tests

Variable	ADF level p	PP level p	Level conclusion	ADF 1st-diff p	PP 1st-diff p	Order
POV	0.0000	0.0000	Stationary	—	—	I(0)
DFI	0.9248	0.9832	Non-stationary	0.0065	0.0000	I(1)
IQ	0.1212	0.0000	Mixed at level	0.0000	0.0000	I(1)
GDPPC	0.9998	0.9735	Non-stationary	0.0000	0.0000	I(1)
TOP	0.0001	0.0054	Stationary	—	—	I(0)
EDU	0.0011	0.0000	Stationary	—	—	I(0)
FD	0.1798	0.0654	Non-stationary	0.0000	0.0000	I(1)

Source: Analysis Report (2026).

Tables 6 shows mixed orders of integration based on the Fisher-type panel unit-root tests. The Fisher-type panel unit-root tests were evaluated at the 5% significance level. The null hypothesis of a unit root is rejected when the reported p-value is below 0.05. Accordingly, POV, TOP and EDU are classified as I(0) because both their ADF and PP tests are significant at level. Specifically, POV records p = 0.0000 for both tests, TOP records p = 0.0001 and 0.0054, while EDU records p = 0.0011 and 0.0000. DFI, GDPPC and FD are non-stationary at level because their ADF and PP p-values exceed 0.05, but they become stationary after first differencing; hence, they are classified as I(1). IQ presents mixed evidence at level: the ADF test is insignificant (p = 0.1212), whereas the PP test is significant (p = 0.0000). To ensure consistency, IQ is conservatively classified as I(1) because both first-difference tests are significant at p = 0.0000. Overall, the variables comprise a mixture of I(0) and I(1) processes, with none integrated of order two.

Table 7. Panel Cointegration Tests for the Reported Regressor Set: DFI, IQ, GDPPC and FD

Test	Specification/statistic	Test statistic	p-value	Decision
Pedroni	Modified PP t, no trend	1.8660	0.0310	Reject H0
Pedroni	PP t, no trend	0.8942	0.1856	Fail to reject H0
Pedroni	ADF t, no trend	1.6686	0.0476	Reject H0
Pedroni	Modified PP t, time trend	3.3511	0.0004	Reject H0
Pedroni	PP t, time trend	1.6618	0.0483	Reject H0
Pedroni	ADF t, time trend	1.7202	0.0427	Reject H0
Kao	Modified DF t	-6.5601	0.0000	Reject H0
Kao	DF t	-1.2598	0.1039	Fail to reject H0
Kao	ADF t	-3.1868	0.0007	Reject H0
Kao	Unadjusted modified DF t	-6.5583	0.0000	Reject H0
Kao	Unadjusted DF t	-1.2592	0.1040	Fail to reject H0
Westerlund	Variance-ratio test	-1.8416	0.0328	Reject H0

H0 = no cointegration. Source: Analysis Report (2026)

The reported cointegration tests were presented in Table 7 which for DFI, IQ, GDPPC and FD provide predominantly supportive, though not unanimous, evidence of long-run association.

Table 8. Panel Regression Results

Variable	Fixed Effect	p-value	Random Effect	p-value
DFI	6.968***	0.000	6.819***	0.000
IQ	273.2***	0.005	2.343	0.976
GDPPC	0.750***	0.000	0.640***	0.003
TOP	3.799***	0.000	2.420***	0.003
EDU	-0.00519	0.994	0.258	0.716
FD	4.095**	0.014	1.251	0.401
Constant	-570.3***	0.000	-289.7***	0.008
N	620		620	
R^2	0.627			
Adjusted R^2	0.611			

** p < .10, ** p < .05, *** p < .01. Source: Analysis Report (2026)*

Table 8 reproduces the baseline panel regression results. DFI is positive and statistically significant in both specifications: 6.968 (p = 0.000) under fixed effects and 6.819 (p = 0.000) under random effects. In the fixed-effects model, IQ, GDPPC, TOP and FD are also positive and significant, whereas EDU is insignificant. On this basis, the positive DFI coefficient is interpreted as an association between greater mobile-money account ownership and higher consumption-based welfare, rather than as direct evidence of poverty reduction or a strictly causal effect.

Table 9. Hausman Specification Test

Statistic	Value
Chi-square test value	56.188
p-value	0.000
Decision	Fixed effects preferred

Source: Analysis Report (2026)

The Hausman test reported in Table 9 yields χ^2 = 56.188 (p = 0.000). The null that the random-effects estimator is appropriate is therefore rejected, so the study uses fixed effects for the main inference.

Table 10. DCCE Long-Run Model

Variable	Coefficient	Standard Error	Significance
DFI	2.642**	1.332	p < .05
IQ	163.5	145.2	Not significant
GDPPC	0.508***	0.179	p < .01
TOP	5.071	3.901	Not significant
EDU	-0.412	0.788	Not significant
FD	5.139**	2.134	p < .05
N	620		

** p < .10, ** p < .05, *** p < .01. Source: Analysis Report (2026)*

In Table 10, the DCCE long-run model provides a positive and statistically significant DFI estimate of 2.642 at the 5% level. GDPPC is also positive and significant (0.508, $p < .01$), while FD is positive and significant (5.139, $p < .05$). IQ, TOP and EDU are not statistically significant. Relative to the fixed-effects estimate, the smaller DFI coefficient indicates that the estimated magnitude is sensitive to model structure. Within the DCCE specification, DFI is positively associated with the consumption-based welfare proxy after allowing for dynamic and common-factor effects. This result is one component of the overall evidence and should be interpreted together with the insignificant DFI estimates in the CS-ARDL specification and the short-run PMG result.

Table 11. PMG Error-Correction and Short-Run Estimates

Variable	Coefficient	Std. Error	t-statistic	p-value	Sig.
ΔPOV(-1)	-0.1998	0.0399	-5.011	0.0000	***
ΔDFI	-2.1805	1.9727	-1.105	0.2695	
ΔIQ	-37.4019	29.7894	-1.256	0.2098	
ΔTOP	4.0741	0.8862	4.597	0.0000	***
ΔEDU	1.2336	0.5553	2.222	0.0267	**
ΔFD	0.3178	1.8948	0.168	0.8668	
ΔFD(-1)	4.0008	1.8612	2.150	0.0320	**
ΔGDPPC	0.5953	0.0160	37.094	0.0000	***
ΔGDPPC(-1)	0.1242	0.0296	4.201	0.0000	***
ECT(-1)	-0.1957	0.0277	-7.064	0.0000	***

** p < .10, ** p < .05, *** p < .01. Source: Analysis Report (2026)*

In Tables 11, the PMG estimates distinguish the short-run and long-run DFI coefficients. In the underlying dynamic specification, the current DFI coefficient is -2.1805 and insignificant ($p = 0.2695$), while DFI(-1) is 5.6450 and significant at the 1 per cent level ($p = 0.0050$). In the error-correction representation shown in Table 11, ΔDFI remains negative and insignificant, whereas the error-correction term is -0.1957 and highly significant. The negative ECT indicates convergence within the PMG specification, with approximately 19.57 per cent of disequilibrium corrected per period.

Table 12. PMG Long-Run Coefficients

Variable	Coefficient	Std. Error	t-statistic	p-value	Sig.
DFI	17.7075	7.6521	2.314	0.0210	**
IQ	-191.1649	150.6759	-1.269	0.2050	
TOP	0.7790	2.4400	0.319	0.7496	
EDU	6.3052	2.8375	2.222	0.0266	**
FD	-6.6835	3.9115	-1.709	0.0880	*
GDPPC	0.5901	0.0418	14.135	0.0000	***
Constant	-327.9310	232.7683	-1.409	0.1594	

The thesis also reports $R^2 = 0.9771$, adjusted $R^2 = 0.9766$, $F = 1840.255$ ($p = 0.0000$) and Durbin-Watson = 2.0539 for the PMG dynamic model. Source: Analysis Report (2026).

The PMG long-run result in Table 12 shows DFI = 17.7075 with p = 0.0210. Thus, within the PMG model, the immediate DFI change is not statistically significant while the estimated long-run association is positive and significant. This model-specific result should not be treated as conclusive evidence of a general long-run effect because the CS-ARDL DFI coefficients are statistically insignificant.

Table 13. CS-ARDL Long-Run Model

Variable	Coefficient	Standard Error	Significance
L.POV	0.0178	0.122	Not significant
DFI	2.386	2.723	Not significant
L.DFI	3.293	5.239	Not significant
IQ	-42.19	135.0	Not significant
L.IQ	155.7	176.7	Not significant
GDPPC	0.609***	0.115	p < .01
L.GDPPC	-0.0627	0.0546	Not significant
FD	4.691***	1.565	p < .01
L.FD	-0.219	4.323	Not significant
N	589		

** p < .10, ** p < .05, *** p < .01. Source: Analysis Report (2026)*

In Table 13, the CS-ARDL result is important because it prevents the evidence from being overstated. DFI is positive in both its current and lagged forms, with coefficients of 2.386 and 3.293, respectively, but neither is statistically significant. IQ is also insignificant. By contrast, GDPPC (0.609, p < .01) and FD (4.691, p < .01) are positive and significant. Therefore, the positive DFI association is present and statistically significant in the fixed-effects model, the DCCE estimator, and the PMG long-run coefficient, but CS-ARDL does not statistically confirm it. The appropriate conclusion is therefore mixed and model-dependent cross-estimator evidence rather than uniform support for a long-run DFI effect. The results do not support a claim that every estimator identifies a statistically significant DFI association. The fixed-effects estimate (6.968, p < .01) and DCCE estimate (2.642, p < .05) are positive and significant, and the PMG long-run coefficient (17.7075, p = .0210) is also positive and significant. By contrast, the PMG short-run DFI change is insignificant and the CS-ARDL current and lagged DFI coefficients are positive but insignificant. The empirical evidence is therefore mixed and model-dependent: DFI is associated with higher consumption-based welfare in the fixed-effects, DCCE and PMG long-run specifications, but this association is not statistically significant in the PMG short run or in the CS-ARDL robustness model. The pattern is compatible with a gradual welfare mechanism, but it does not by itself establish that such a mechanism is causal or universal across specifications.

Discussion of Findings

The evidence indicates a positive association between digital financial inclusion and the consumption-based welfare proxy in some specifications, but it is not uniform across estimators. The fixed-effects and DCCE estimates are positive and significant, and so is the PMG long-run coefficient. However, the PMG short-run DFI change is not significant, while the CS-ARDL current and lagged DFI coefficients are positive but not significant. The evidence is therefore model-dependent rather than sufficient for an unqualified acceptance of a general DFI effect. The positive association is strongest in the baseline within-country and selected long-run specifications, not as an immediate relationship invariant to model choice. Any interpretation in terms of gradual financial utilisation and accumulated welfare transmission should consequently be presented as a plausible explanation of the pattern, not as a causal mechanism established by the estimates.

These findings align with Financial Intermediation Theory. Mobile money and related digital services can reduce distance, search and transfer costs, make it easier to receive funds and increase access to basic financial transactions. But the theory is most convincing here in its dynamic sense. Lower transaction costs are an opportunity, not a payoff. Households need to use the account

repeatedly, choose to save or receive transfers through it, build trust in agents and platforms, and potentially convert transaction histories into credit or enterprise opportunities. The larger PMG long-run coefficient is thus consistent with cumulative intermediation rather than one-off account opening. It also explains why policies evaluated too soon after rollout may find weak effects even when longer-run welfare gains eventually emerge. This largely aligns with Omar and Inaba (2020) and Kumar and Qin (2023), who find poverty-reducing effects of broader financial inclusion, but offers a more specific digital interpretation. It is also consistent with Wang and He (2020), Ouyang et al. (2022) and Liu and Guo (2023), whose household evidence identifies risk management, credit relief, entrepreneurship and consumption as pathways from digital finance to lower poverty vulnerability. But those studies are concentrated on China, where digital platforms are deeply embedded in commerce and daily life. Hence, the present SSA evidence is informative, as it suggests the underlying welfare mechanism is not unique to the Chinese context, although the size and speed of the effect are likely to differ.

This finding aligns closely with the findings of Iwedi et al. (2024), Adefabi (2025), Osuma (2025), and Udo and Akpan (2026) in Africa. Iwedi et al. link mobile money and digital payment channels to consumption expenditure, which is particularly relevant as the present study also operationalises welfare through household consumption. Adefabi, Udo and Akpan (2025) also find that frequency of use, reliability, affordability, and Institutional support matter. These results help interpret the long-run coefficient in this paper. If depth of usage matters, then it is no surprise that the immediate PMG effect is insignificant. An account has to move from registration to regular use, and from regular use to economically meaningful use, and that takes time. However, the contradictory evidence still counts. Simon-Ilogho and Moloi (2026) in their analysis of SSA, find that mobile money usage does not significantly reduce poverty. Saka et al. (2025) similarly find indirect rather than direct welfare effects in Ghana. These studies suggest the present positive result is not universal. One explanation is measurement. Owning a mobile money account captures access to the digital ecosystem, but not whether the account is active, how often it is used, or whether transactions are productive. Another is outcome choice. Consumption expenditure, poverty headcount, food insecurity and human development capture different aspects of welfare and can respond at different speeds. A third is affordability and infrastructure. The same nominal account may be useful in areas with dense agents and reliable networks but largely inactive where users face weak connectivity, high fees, or cash shortages at agent points.

The contrast between DFI and general financial development is especially telling. The fixed-effects and DCCE estimates suggest a positive association between financial development and poverty reduction, whereas the PMG long-run estimate is negative and only marginally significant. The unstable financial-development coefficient suggests that financial deepening can occur without broad inclusion. In government-controlled sectors, large firms and wealthy households may see growth in credit and financial assets, with little direct benefit to poor populations. DFI, by contrast, is measured at the level of adult mobile money participation and therefore lies closer to the access margin. This does not prove that all digital finance is pro-poor, but it does show why broad financial-depth indicators should not substitute for inclusion measures.

GDP per capita remains robustly positive across estimators, which sets an important boundary for policy interpretation. Digital finance is not a replacement for economic growth, productive employment or rising household income. Its contribution is more plausibly complementary. Growth creates income and market opportunities; digital finance can reduce the friction involved in receiving, storing, transferring and deploying resources. If growth is concentrated in capital-intensive sectors or fails to raise low incomes, digital accounts will not compensate for weak labour demand. Conversely, when households participate in growing markets, digital finance can make that participation more efficient and resilient.

Education provides another temporal parallel. It has a significant and positive long-run coefficient on PMG, while the coefficient on its fixed effects is insignificant. Thus, both education and DFI seem to serve partly as stock capabilities, rather than as immediate welfare shocks. Education takes time to affect employability and productivity; digital financial participation takes time to affect saving, transactions, and enterprise behaviour. This analogy suggests a broader methodological lesson in the paper: static significance tests can be misleading when development mechanisms work through incremental adoption and adjustment.

5. Conclusion and Recommendations

This paper finds model-dependent evidence of a positive association between digital financial inclusion and a consumption-based welfare outcome used as a proxy for poverty reduction in Sub-Saharan Africa. The DFI coefficient is positive and significant in the fixed-effects model across 31 countries and 620 country-year observations, the DCCE estimate is also positive and significant, and the PMG long-run coefficient is positive and significant. However, the PMG short-run DFI change is statistically insignificant, and the CS-ARDL current and lagged DFI coefficients are also statistically insignificant. The overall evidence should therefore be described as

suggestive and model-dependent rather than strong or unambiguous. It indicates a positive association in selected baseline and long-run specifications, while not establishing an immediate, uniformly robust or strictly causal welfare effect across estimators.

The policy implication is that governments, central banks, telecommunications regulators and providers should measure digital inclusion by active and useful participation, not by registrations. Reducing transaction costs, expanding rural agent networks, increasing network reliability, reducing the burden of appropriate identification requirements, and increasing digital financial literacy can help to move from nominal access to repeated use. When this reduces costs and improves traceability, social transfers and payments for agriculture and microenterprise transactions can also be channelled through trusted digital channels. At the same time, digital credit should be carefully supervised so easier access does not lead to high-cost indebtedness.

The findings also indicate that digital finance should not substitute policies that encourage income and productive opportunity. GDP per capita is still a good predictor of welfare, but education is more relevant in the long run. Digital finance is therefore most likely to reduce poverty when households have economic activity to transact around, the skills to use services effectively, and reliable infrastructure through which they can access the services. Future work should measure transaction intensity, metrics of active accounts, and household-level outcomes where possible; disaggregate effects by rural and urban populations; and test whether long-term benefits differ by gender, income group, and subregion. It should also test poverty headcount or multidimensional poverty measures along with consumption-based welfare indicators to see whether the positive DFI relationship holds under alternative definitions of poverty reduction.

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