JOURNAL OF CULTURAL ANALYSIS AND SOCIAL CHANGE

Journal of Cultural Analysis and Social Change,
2025, 10(4), 1105-1116
ISSN: 2589-1316

The Causal Nexus Between Digital Financial Inclusion and Economic Growth in Sub-Saharan Africa

Abdallah Sayed Mossalem Ahmed Elshafei[1*], Doaa M. H. Ahmed[2], M. M. Abd El-Raouf[3], M. A. El-Qurashi[3]

[1]*Department of Basic Sciences, Higher Institute for Administrative Sciences, Belbeis, AlSharkia, Egypt*
[2]*Department of Insurance and Risk Management, College of Business, Imam Mohammad Ibn Saud Islamic University (IMSIU), , Riyadh, Saudi Arabia*
[3]*Institute of Basic and Applied Science, College of Engineering and Technology, Arab Academy for Science, Technology and Maritime Transport, Abu Quir Campus, Alexandria, Egypt*

***Corresponding Author:** abedo_sayed@yahoo.com

Citation: Elshafei, A. S. M. A., Ahmed, D. M. H., El-Raouf, M. M. A., & El-Qurashi, M. A. (2025). The Causal Nexus Between Digital Financial Inclusion and Economic Growth in Sub-Saharan Africa. *Journal of Cultural Analysis and Social Change*, *10*(4), 1105–1116. https://doi.org/10.64753/jcasc.v10i4.2987

Published: December 07, 2025

ABSTRACT

This analysis examines the causal relationship between digital financial inclusion and economic performance in Sub-Saharan Africa, a region experiencing significant financial access constraints. The theoretical framework suggests that digital financial services lower information barriers and transaction expenses, facilitating improved capital distribution and business development. The study develops a new composite index measuring digital financial inclusion through principal component analysis, combining multiple indicators across access, usage, and quality dimensions. To test the claim on a panel data consisting of 35 SSA countries spanning from 2004 to 2022, and solving the endogeneity problem arising from reverse causality and unobserved heterogeneity, a two-step system generalized method of moments (GMM) estimator is adopted. Our results provide robust evidence for a positive causal relationship. We find that a one standard deviation increment in the DFII leads to a statistically significant increase of 0.154 percentage points in annual GDP per capita growth. The methodological approach used in this analysis—specifically, the development of a comprehensive, multi-dimensional index alongside the deployment of a dynamic panel estimator to mitigate the risks associated with endogeneity—establishes a robust foundation for causal inference. This approach significantly elevates the scientific credibility of the findings, setting them apart from prior research that was largely constrained to mere correlational analysis. Furthermore, the stability of these conclusions is definitively confirmed by their successful replication across diverse model specifications and their satisfactory performance on all requisite post-estimation diagnostic criteria. Consequently, the evidence presented confirms that Digital Financial Inclusion (DFI) functions as a fundamental driver of economic expansion.

Keywords: Digital financial inclusion, Economic growth, Financial intermediation, System GMM, Endogenous growth, Sub-Saharan Africa, Fintech
JEL Classification: O16, O33, O55, G21.

INTRODUCTION

Financial system limitations in Sub-Saharan Africa present substantial challenges to regional economic advancement objectives. Credit markets in the region frequently demonstrate limited activity, restricting their ability to allocate capital efficiently and achieve meaningful financial system development. This stagnation is compounded by the prevalence of disproportionately high intermediary margins, which have consistently inhibited both capital formation and the fostering of productive investments through formal institutional channels (Levine, 2005; Beck & Cull, 2023). Fundamentally, the traditional model of branch-based banking proved economically unsustainable, failing to overcome the monumental structural barriers inherent in the region: vast geographical distances, sparse population densities, and the extraordinarily high fixed costs associated with servicing low-income, rural populations (Demirgüç-Kunt et al., 2018). The subsequent widespread exclusion from formal finance has, in turn, exacerbated income informality, severely stymied the mobilization of domestic savings, and redirected available credit away from potentially high-growth, productive enterprises. Consequently, the trajectory of financial service provision has necessitated a definitive shift from brick-and-mortar institutions to agile digital platforms. Digital Financial Inclusion (DFI) is recognized as a disruptive force capable of effectively removing these entrenched market inefficiencies (Ozili, 2021). By leveraging digital technologies, DFI ensures the delivery of financial services that are affordable, accessible, and appropriate to those segments of the population historically underserved or entirely excluded by conventional methods. The core advantage lies in mobile money and digital networks, which bypass the necessity for legacy physical infrastructure, fundamentally altering the cost-benefit calculus for mass-market financial servicing. At the microeconomic level, a growing body of empirical literature confirms the positive impact of specific DFI tools, notably mobile money, on household welfare and resilience. Several studies show good effects of consumption smoothing, shock resilience, or poverty alleviation, sending overseas remittances with ease-witnessing the M-Pesa case in Kenya has become a driver of great interest (Suri & Jack, 2016; Batista & Vicente, 2020). However, a significant gap exists in the macroeconomic literature: the transmission channels through which these effects at the micro-level aggregate to cause economy-wide growth have not been sufficiently quantified or rigorously tested by causality methods. Adding to these, the extant macro-level studies suffer from two major limitations: first, with single-proxy measures (like number of mobile money accounts or ATM density) that cannot describe the complex multidimensional reality of DFI as an ecosystem spanning access, usage, and quality: and, secondly, they give rise to causality identification problems: financial development and economic growth are mutually determined, leading to a spurious correlation that may be mistaken for causality (Evans & Adeoye, 2020; Tchamyou et al., 2019). This study therefore aims to thoroughly investigate the causal relationship between the magnitude of digital financial inclusion and economic growth in SSA, while properly accounting for endogeneity using instrumental variables. Factors affecting the magnitude of digital financial inclusion and economic growth in Africa must be known and accounted for. Our position is that constructing such a holistic index with strong econometric methods, which properly treat the issues of endogeneity, will provide much stronger evidence on this critical relationship. Consequently, three objectives can be distilled into specifying these investigations: To provide a methodologically robust assessment, this study first develops a multi-dimensional composite index of Digital Financial Inclusion (DFI), systematically capturing the fundamental conceptual facets of access, usage, and quality. The causal effect of this index on per capita GDP growth is then rigorously disentangled through the application of the dynamic System Generalized Method of Moments (System GMM) estimator, an approach specifically chosen to explicitly control for pervasive econometric challenges, including endogeneity, reverse causality, and unobserved country-specific time-invariant heterogeneity. The research proceeds by elucidating the primary economic channels underpinning this transmission mechanism and culminates in the formulation of concrete evidence-based policy (EBP) recommendations for regional regulators and policymakers.

The structure of the paper proceeds as follows. Section 2 offers a thorough review of the theoretical and empirical literature, which sets the stage for the analytical framework adopted. Section 3 outlines the empirical strategy, including model specification, construction of the DFI index, estimation technique, and data sources. Section 4 presents the core empirical results, discusses economic meanings of the results, and carries out various robustness tests. Then, Section 5 will summarize the principal findings before discussing policy implications and avenues of future research.

LITERATURE REVIEW AND THEORETICAL FRAMEWORK THEORETICAL UNDERPINNINGS OF THE FINANCE-GROWTH NEXUS

Financial system development represents a crucial determinant of economic growth in contemporary development theory. In his classic work, Joseph Schumpeter (1911) highlighted the critical role of financial intermediaries, particularly banks, in promoting economic development by identifying and funding innovative entrepreneurs in the process of creative destruction, thereby channeling capital into its most productive use. This idea was later expanded upon by McKinnon (1973) and Shaw (1973), who stated that financial repression, in the form of interest rate ceilings, high reserve requirements, and directed credit programs, hinders the mobilization of savings, discourages investment, and leads to inefficient capital allocation. They suggested that financial liberalization would lead to deeper financial systems, better investments, and faster economic growth. Within the framework **of** endogenous growth theory (Romer, 1990; Aghion and Howitt, 2009), this nexus is analyzed on a more formal theoretical platform. Endogenous growth models demonstrate that financial development influences the **steady-state growth rate** of an economy, not merely altering the level of output. The core function of the financial system is to diminish information costs, transaction costs, and other market frictions, thereby facilitating the efficient flow of capital toward ventures possessing the highest expected marginal productivity. Furthermore, the system provides crucial incentives for innovation, specifically by fostering research and development (R&D) and human capital formation, which inherently lowers the cost of external financing for such endeavors. Digital Financial Inclusion (DFI) significantly revitalizes and amplifies these classical growth mechanisms by directly addressing the fundamental frictions that have constrained traditional finance in developing regions. Interconnected Transmission Channels, the most immediate and fundamental impact of DFI is the radical decline in the cost of executing financial transactions. Mobile money platforms, for instance, have drastically minimized the expense of transferring, storing, and saving value. This cost reduction makes small, frequent transactions economically viable for both providers and users, overcoming the previously prohibitive fixed costs that led to the exclusion of low-income populations (Jack & Suri, 2011). Secondly, DFI generates ample, real-time data trails—a reliable digital footprint—on user cash flow and behavior, which facilitates the development of novel credit scoring and risk assessment methodologies. From the lenders perspective, DFI mitigates the problems of adverse selection (screening out poor risks) and moral hazard (monitoring borrower actions), enabling the assessment of creditworthiness for individuals and SMEs who otherwise lack collateral or credit histories (Berg et al., 2020).

Thirdly, digital platforms leverage powerful network externalities. The utility of a mobile payment network multiplies exponentially as more individuals and businesses join, creating a positive feedback loop that drives rapid adoption, deepens market penetration, and facilitates the construction of a comprehensive digital economic ecosystem (Gomber et al., 2018). Figure 1 illustrates this conceptual framework, showing that DFI acts via interconnected channels that reduce transaction costs and information asymmetries. The interrelated transmission channels for economic growth include: Enhanced Savings Mobilization: Lower friction and increased convenience pull latent capital (often held outside the formal system) into loanable funds, Superior Credit Allocation: Reduced informational barriers allow DFI to efficiently match savings with productive investment opportunities, particularly for innovative SMEs, Improved Productivity and Efficiency: Digital payments streamline business operations and reduce time and costs associated with managing cash, freeing up resources for core productive uses, Risk Mitigation and Sharing: Access to digital savings and insurance products empowers households and firms to buffer economic shocks, smooth consumption, and undertake higher-return investments. In other words, the formalization of the informal economy entails the inclusion of those informal activities as a digitally traceable economic transaction, thus enlarging the tax base, improving the quality of economic data, and higher measured GDP (Sahay et al., 2020).

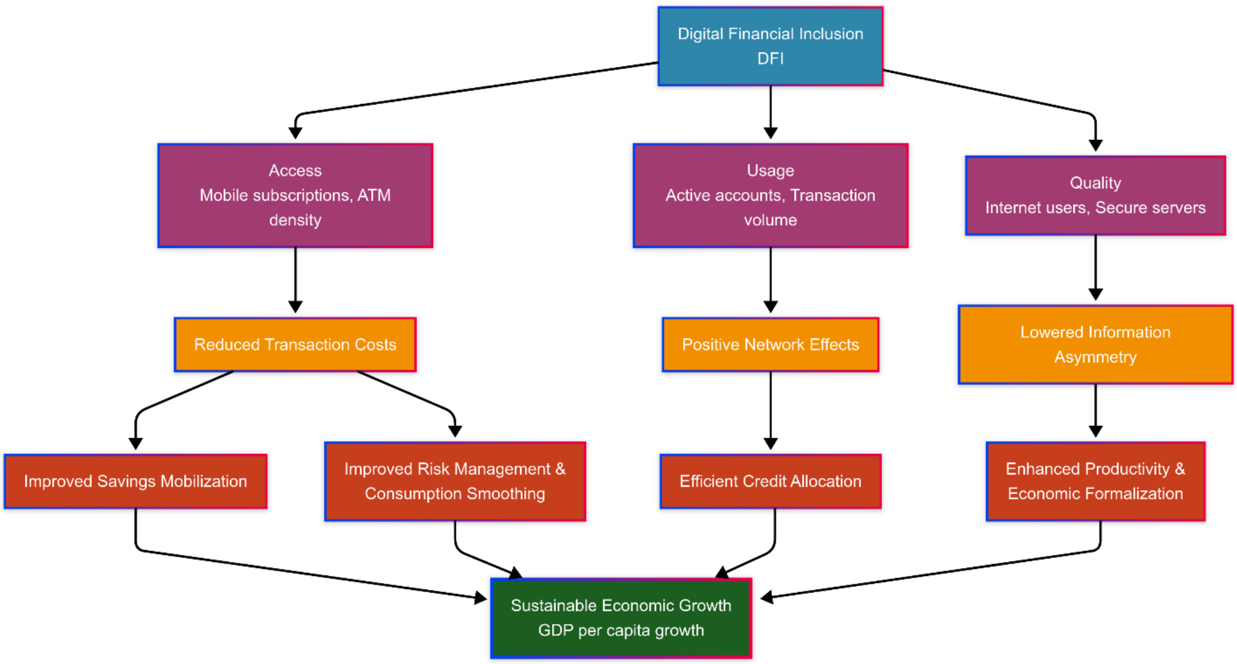

Figure 1. The Conceptual Framework Linking Digital Financial Inclusion to Economic Growth in Sub-Saharan Africa.

Empirical Evidence: Micro Foundations and Macro Correlations

The theory-backed channels find heavy empirical but micro-level support in the literature. There is an increasing amount of evidence, at the household and firm level, to support the contention that mechanisms depicted in Figure 1 are at work. Seminal studies from the period of M-Pesa implementation in Kenya established that Digital financial services substantially lower transaction expenses, allow for sharing of risks, and generally improve welfare. Suri and Jack (2016) showed that M-Pesa increased per capita consumption and saved households from poverty. These micro-foundations are very important, as they prove the possibility of aggregate economic effects. However, a major question remains: do these micro-level effects aggregate at the macroeconomic level into a measurable, causal impact on growth? At the macro level, studies have often been limited by measurement issues and the inability to address endogeneity fully. This research addresses methodological limitations by empirically examining the primary hypothesis that digital financial inclusion exerts a positive causal influence on macroeconomic growth performance within the conceptual framework that DFI indeed has a positive causal impact on GDP per capita growth at the macroeconomic level.

From the empirical literature, these supporting arguments are derived, although they are often highly micro structured or methodologically constrained. The evidence has been cited as more convincing on the microeconomic level. Some of the more important studies have been done on M-Pesa in Kenya. Suri and Jack (2016) used household survey data over a period of years to show that access to M-Pesa increased levels of per capita consumption and raised 2% of Kenyan households out of extreme poverty. The channels were enhanced risk-sharing (remittances) and more movement away from subsistence farming to activity engaged in business productivity. The saving and resilience effects were shared by Batista and Vicente (2020) between smallholder farmers in Mozambique. This cumulative body of research, therefore, provides a robust micro-level empirical foundation supporting the assertion that DFI enhances welfare outcomes. Correspondingly, various cross-country and panel studies have documented a positive correlation between measures of financial inclusion and macroeconomic growth. Kim et al. (2018) established this positive association among OIC nations, while Evans and Adeoye (2020) found a comparable linkage across the African continent. Nevertheless, the macro-level literature is compromised by two critical methodological drawbacks: Measurement Inadequacy: A significant portion of studies relies on proxies ill-suited for the digital age, such as per capita bank or ATM densities. These metrics fail to capture genuine digital financial inclusion, which is fundamentally predicated on digital access and active usage, rather than simply physical infrastructure availability, Endogeneity: Theoretically, the relationship between finance and economic growth is inherently bidirectional. While a clear finance-for-growth nexus is evident, higher incomes also drive greater concurrent demand for, and accelerated adoption of, financial services. Reverse causality is left largely unaddressed in most of these studies, as is omitted variable bias, for example, improvement of institutions in general may cause both more finance and more growth rendering correlational inferences unreliable (Tchamyou, 2019). Multidimensionality: Recently, studies have agreed that DFI is essentially highly multidimensional and latent in nature (Ozili, 2021: Della Peruta, 2018). A common limitation among studies endeavoring to construct similar composite indices is the absence of a rigorously articulated identification strategy, which is essential for establishing credible claims of causality.

Contribution of the Present Study

The overall strategic thrust of this research is explicitly designed to address and close these aforementioned gaps through three crucial contributions: A Contemporary, Multi-Dimensional Index: Moving beyond reductive single-proxies, a novel and standardized DFI index is systematically developed utilizing the most current available data (2004–2022). This index incorporates six distinct indicators spanning the core dimensions of access, usage, and quality, providing a refined measure of the evolving DFI ecosystem. Robust Causal Identification: The study employs the two-step System Generalized Method of Moments (System GMM) estimator, optimally suited for dynamic panel analysis. This application rigorously controls for the complexities of financial development endogeneity, reverse causality, dynamic panel bias (Nickell bias), and unobserved country-specific fixed effects, thereby yielding causal estimates that are inherently more credible than those derived from preceding correlation-based studies. Comprehensive and Timely Regional Analysis: We offer a broad, current regional analysis focused exclusively on 35 SSA countries during a period of intense digital transformation. This focused regional scope enhances the homogeneity of the analysis, providing highly relevant and timely evidence-based insights for policymakers across the continent.

METHODOLOGY AND DATA

Empirical Model

Economic growth typically exhibits persistence, with current performance levels influenced by historical economic outcomes. The dynamic panel model expressing this functional relationship is as follows:

$\text{GDP Growth}_{it} = \alpha + \delta\, \text{GDP Growth}_{i,t-1} + \beta\, \text{DFII}_{it} + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it}$ Where:

- i indexes countries, and t indexes the time period (year).

- GDP Growth_{it} is the annual percentage growth rate of GDP per capita (constant 2015 US$), which is the main dependent variable.
- GDP $Growth_{i,t-1}$ is the one-period lag of the dependent variable, included to capture persistence and dynamics.
- DFII_{it} is the constructed Digital Financial Inclusion Index (DFII), the variable of chief interest.
- X_{it} is a vector of control variables, including:
- Investment (GDP): To capture capital accumulation.
- Government Consumption (GDP): To account for the size of the public sector and potential crowding-out effects.
- Trade Openness: Sum of exports and imports as a percentage of GDP, to account for integration into the global economy.
- Inflation (log): Annual percentage change of the consumer price index (log-transformed) for macroeconomic stability.
- Human Capital Index: Based on an index of years of schooling and returns to education, meant to account for the quality of the labor force.
- μ_i represents the unobserved country-specific fixed effects.
- λ_t represents the unobserved time-specific fixed effects (time dummies).
- ϵ_{it} is the idiosyncratic error term.

To isolate the effect of digital financial inclusion, we control for a vector of variables, Xit, which includes: investment (% of GDP), government consumption (% of GDP), trade openness, inflation (log), and the human capital index, as detailed in Equations 109-113.

In order to capture potential structural breaks, especially the global economic shock caused by the COVID-19 pandemic, a dummy variable was introduced in the robustness checks for the years 2020 and 2021. As discussed in Section 4.2, the results show that the main conclusions hold even after considering this large exogenous shock.

Construction of the Digital Financial Inclusion Index (DFII)

Since DFI is a latent variable and, therefore, cannot be observed directly, we build the composite index using Principal Component Analysis. This analysis is one of the statistical techniques that utilize dimension reduction by transforming a set of correlated variables into a set of uncorrelated principal components ordered by the amount of original variance they explain. We chose six indicators that together represent the three broad dimensions of DFI Access: ... ATM density (ATMs per 100,000 adults): Traditionally an indicator for the realm of conventional banking, this indicator remains, however, quite essential in the context of SSA as it does allow for cash-in/cash-out operations, which are vital for the functioning of a digital financial ecosystem. ATM density thus finds its place in the set of indicators due to the hybrid nature of digital financial systems in developing economies, where physical and digital infrastructures coexist and complement each other.

that enable digital financial transactions, especially for cash-in and cash-out operations, which are essential for integrating informal economies into the digital financial system. While ATM density is one of the conventional indicators for infrastructure, we argue for its inclusion in our index of digital inclusion for two major reasons that are pertinent to the SSA context. First, it provides a critical node for cash-in/cash-out (CICO) operations in digital finance ecosystems, implying that it acts as an interface between physical cash and digital value. Second, in many SSA countries, digital and physical infrastructures complement each other rather than act as one or the other. To further confirm the robustness of our index, we carried out a sensitivity analysis with the reconstruction of the DFII with the exclusion of the variable of ATM density. The results of the analysis (provided on request) continued to provide a qualitative confirmation that our results were not driven by this parameter alone, a feature particularly relevant in the SSA **context.** Usage: Usage intensity of the services available, Active mobile money accounts (per 1,000 adults): Measures the adoption of the core DFI platform, Volume of mobile money transactions (% of GDP): Measures economic significance and intensity of use, **Quality:** Reflecting the resilience and sophistication of the digital infrastructure, Individuals using the Internet (% of population): A prerequisite for more sophisticated digital financial services over and beyond basic USSD, Secure Internet servers (per 1 million people): Proxy indicator for the security and sophistication of the national digital infrastructure.

We selected the first principal component to create the DFII since it was the only one having an eigenvalue greater than 1 according to the Kaiser criterion and represented nearly 68% of the total variance. The component loadings display the correlation of each indicator with the principal component and are shown in Table 1. All loadings being positive and significant indicate that each indicator is positively contributing to the composite index. The index is standardized to zero mean and unit variance.

Table 1 presents the results of the principal component analysis conducted to construct the index of digital financial inclusion. The first principal component on which the DFI index is based explains almost 68 percent of the total variation in the six indicators. The indicator loadings show the correlation of each indicator with the principal component. All loadings being positive and significant imply that each indicator contributes in a positive way to the composite index. The index is standardized to zero mean and unit variance.

Table 1. Principal Component Analysis for DFI Index Construction.

Indicator	Category	Component Loading (1st PC)	Eigenvalue	Variance Explained	Cumulative Variance
Mobile cellular subscriptions (per 100 people)	Access	0.41	4.08	68.0%	68.0%
ATM density (per 100,000 adults)	Access	0.39	-	-	-
Active mobile money accounts (per 1,000 adults)	Usage	0.43	-	-	-
Volume of mobile money transactions (% of GDP)	Usage	0.42	-	-	-
Individuals using the Internet (% of population)	Quality	0.40	-	-	-
Secure Internet servers (per 1 million people)	Quality	0.38	-	-	-

Source: Authors calculations based on data from World Bank, GSMA Intelligence, and Penn World Table
Note: The first principal component explains 68% of total variance, with eigenvalue > 1 (Kaiser criterion)

The selection of these six indicators is grounded in established digital financial inclusion theoretical frameworks (Ozili, 2021: Della Peruta, 2018) to ensure that it addresses all facets of access, usage and quality. The loadings, all positive and significant, can be interpreted as the relative weight of the indicator in the composite index. For example, Active mobile money accounts has the highest loading (0.43), which suggests that the intensity of usage is a particularly significant dimension in the DFI realm.

Estimation Technique: The System GMM Estimator

Including lagged dependent variables in regression specifications introduces dynamic panel bias, rendering conventional estimation methods potentially unreliable. To address these endogeneity concerns, we employ the two-step system GMM estimator of Blundell and Bond (1998). Suitable for panels with a small T and large N such as our own (19 years and 35 countries) and a highly persistent dependent variable and potentially endogenous regressors. The system GMM estimator combines the sets of equations into a system: The differenced equation: The regression in first-The differencing procedure accounts for unobserved time-invariant country characteristics (μ_i),The level equation: The original regression in levels, to instrument the endogenous variables, system GMM apply: Lagged levels of the variables as instruments for the differenced equation, Lagged differences of the variables as instruments for the level equation. This method provides additional moment conditions that can enhance efficiency if the variables are persistent. A very careful approach was taken up on the chances of instrument proliferation, which might serve as a spoiler for the power of the Hansen test. which can weaken the power of the Hansen test to detect invalid instruments (Roodman, 2009), we followed a conservative approach. Our baseline model utilizes a carefully selected set of instruments. Furthermore, as a robustness check, we re-estimated the model using a collapsed instrument matrix. In both specifications, the Hansen tests p-value remained well above 0.1, indicating the validity of our instruments. Instruments are accepted under the null hypothesis (p-value > 0.1), - The Arellano-Bond test for autocorrelation: Testing AR(2) or no second-order serial correlation in the differenced error term. A null hypothesis of no correlation is desired (p-value > 0.1). AR(1) or first-order serial correlation is expected and is not a problem by design.

Data Sources and Descriptive Statistics

The analysis covers 35 countries in an unbalanced panel over the period 2004–2022. The selection of countries is primarily driven by data availability for key elements of the Digital Financial Inclusion Index (DFII). To ensure the reliability of the principal component analysis, countries with a significant number of missing observations for the six indicators were excluded, this being also to ensure the reliability of the principal component Analysis.

Since the data is only available up to 2022, the choice of countries and periods would have to be subject to these limitations. Data were compiled from multiple institutional sources including the World Bank development indicators: the World Bank, e.g. WDI time frames-in GDP growth, investment, government consumption, trade openness, inflation, mobile subscriptions, internet users and secure servers; Global Financial Inclusion Database (Global Findex): World Bank (conceptual guidance: underlying data partially); International Monetary Fund, International Financial Statistics (for inflation series); GSM Association, GSMA Intelligence (mobile money accounts and transaction volumes); and Penn World Table (PWT) 10.0 for the human capital index

Table 2. Descriptive Statistics (N = 525 country-year observations).

Variable	Description	Mean	Std. Dev.	Min	Max
GDP per capita growth (annual %)	Annual percentage growth rate of GDP per capita based on constant 2015 US$	1.95	4.12	-31.23	23.51
Digital Financial Inclusion Index	Standardized composite index (mean=0, SD=1) constructed via PCA from six access, usage, and quality indicators	0.00	1.00	-1.89	3.15
Investment (% of GDP)	Gross capital formation as a share of GDP	22.10	8.51	5.20	45.80
Government Consumption (% of GDP)	General government final consumption expenditure as a share of GDP	15.30	5.92	3.10	32.50
Trade Openness (% of GDP)	Sum of exports and imports of goods and services as a share of GDP	72.50	29.81	21.30	189.20
Inflation (annual %, log)	Logarithm of the annual percentage change in the consumer price index	2.10	0.92	-1.22	5.81
Human Capital Index	index based on years of schooling and returns to education (Source: Penn World Table 10.0)	2.10	0.42	1.20	3.10

Source: Data compiled from World Development Indicators (World Bank), GSMA Intelligence, IMF, and Penn World Table (PWT 10.0).

The descriptive statistics indicate substantial variation across the region and hence a good basis for econometric analysis. GDP growth averages a small, positive 1.95%, but the high standard deviation **suggests** that growth experiences are unstable and uneven. The DFII has been standardized and ranges in such a way that some countries are far below the mean level of digital inclusion as others are far above it.

EMPIRICAL RESULTS AND DISCUSSION

Main Results

Table 3. System GMM Estimation Results: The Impact of DFI on Economic Growth (Dependent Variable: GDP per capita growth rate).

Explanatory Variables	Coefficient	Std. Error	p-value
Lagged GDP Growth	0.228	0.051	0.000
Digital Financial Inclusion (DFII)	**0.154**	**0.039**	**0.001**
Investment (% of GDP)	0.192	0.033	0.000
Government Consumption (% of GDP)	-0.088	0.036	0.018
Trade Openness (% of GDP)	0.059	0.026	0.027
Inflation (log)	-0.121	0.029	0.000
Human Capital Index	0.101	0.053	0.059
Model Specification & Diagnostic Tests	**Statistic**	**p-value**	
Hansen Test (J-statistic)	28.74	0.317	
AR(1) Test	-2.51	0.012	
AR(2) Test	-0.75	0.453	
Number of Instruments	32		
Number of Countries	35		

Note: denote significance at the 10%, 5%, and 1% levels, respectively.
Source: Authors own econometric estimation.

The estimation results present findings from the two-step system GMM procedure. Diagnostic examination offers substantial evidence supporting the model specification and instrument selection. The Hansen J-test p-value at 0.317 fails to suggest the invalidity of instruments. The high p-value suggests that the instrument set is valid and avoids the weak instrument problem and possesses still enough power for identification. This finding is further confirmed by robustness checks employing the collapsed instruments. The Arellano-Bond test identifies the existence of first-order serial correlation [AR(1): p-value = 0.012] while establishing the non-existence of second-order serial correlation [AR(2): p-value = 0.453], and this is important for the consistency of the GMM estimator. For the AR(2) test, the null hypothesis is considered that the residuals do not suffer from second-order autocorrelation. At a p-value of 0.453, we do not find evidence of second-order autocorrelation. That is a highly important result for the GMM estimator to be consistent because it confirms the validity of lagged dependent variables as instruments and establishes correct model specification.

The statistically significant and positive coefficient obtained for the lagged dependent variable demonstrates a pronounced persistence in regional growth rates, which robustly validates the methodological necessity of employing a dynamic model. Results for the primary control variables align with conventional economic theory: investment and trade openness are positively correlated with higher growth outcomes, while government consumption and inflation exhibit a detrimental effect. Crucially, the coefficient for the Digital Financial Inclusion Index (DFII) is estimated at 0.154, achieving statistical significance at the 1 percent level. This key finding implies that a one standard deviation increase in the DFII is associated with an annual increase of 0.154 percentage points in per capita GDP growth. This estimate, which is inherently more reliable due to the explicit control for endogeneity, surpasses the findings of previous correlation-based studies.

To elaborate on the economic significance, this effect accounts for approximately 7.9 percent of the average annual GDP per capita growth rate (1.95%) observed within the sample. Put differently, if a country with an average DFII were to improve its standing to match the performance of the top quartile, it could generate an additional 0.3 to 0.4 percentage points in its annual per capita growth rate, a substantial boost for development within the region. The positive coefficient on the Human Capital Index (HCI) is only marginally significant (p-value = 0.059). This marginality likely reflects measurement challenges: the standard HCI, which measures years of schooling, may be an inaccurate or noisy proxy for digital literacy, the true prerequisite skill for effective DFI adoption and use. Alternative explanations include the possibility of a non-linear relationship or mediation by the existing level of digital infrastructure. Therefore, future research is warranted to explore this relationship using more granular measures that specifically operationalize the skills relevant to digital finance.

Robustness Checks

The baseline estimation was subjected to several robustness checks to confirm the validity of our findings. A key test involved addressing potential instrument proliferation, a risk associated with dynamic panel models—by re-estimating the model with a collapsed instrument matrix to minimize the risk of overfitting. Upon performing this test, the coefficient for the Digital Financial Inclusion Index (DFII) remained positive and statistically significant at the one percent level. Furthermore, the p-value for the Hansen J-test consistently exceeded 0.1, thereby affirming the validity of the over-identifying restrictions. This procedure conclusively supports the conclusion that our estimation results are not spurious artifacts of an excessive instrument count. 2. Alternative Estimators: As a further test of robustness, we compared the system GMM against a series of biased estimators to see whether these could actually bound the consistent estimate. The estimates indeed behaved as theorized: Pooled OLS had an upward bias of approximately 0.198 because it fails to account for unobservable country-specific effects and for dynamic panel bias, Fixed-Effects (Within) was biased downward at 0.091 due to Nickell bias in dynamic panels with fixed effects, whereas our system GMM estimate of 0.154 lies reasonably between these two biased estimates and is therefore consistent, which is one way we argue further in its support.

Table 4. Robustness Checks - Alternative Estimators (Dependent Variable: GDP per capita growth rate).

Variable	**System GMM (Baseline)**			**Fixed Effects**			**Pooled OLS**		
	Coeff.	S.E.	p-val.	Coeff.	S.E.	p-val.	Coeff.	S.E.	p-val.
Digital Financial Inclusion (DFII)	0.154	0.039	0.001	0.091	0.043	0.036	0.198	0.035	0.000
Lagged GDP Growth	0.228	0.051	0.000	0.105	0.048	0.029	0.312	0.041	0.000
Investment (% of GDP)	0.192	0.033	0.000	0.145	0.038	0.000	0.223	0.029	0.000
Government Consumption (% of GDP)	-0.088	0.036	0.018	-0.062	0.033	0.060	-0.071	0.031	0.023
Trade Openness (% of GDP)	0.059	0.026	0.027	0.042	0.024	0.080	0.051	0.022	0.021
Inflation (log)	-0.121	0.029	0.000	-0.088	0.025	0.000	-0.095	0.023	0.000
Human Capital Index	0.101	0.053	0.059	0.087	0.049	0.077	0.124	0.050	0.013
Country Fixed Effects	Yes			Yes			No		

Note: denote significance at the 10%, 5%, and 1% levels, respectively. All models include the full set of control variables.
Source: Authors own econometric estimation

Outlier Analysis: To verify that our results were not being driven by a few regional leaders with highly advanced DFI ecosystems (Kenya and Rwanda), we excluded them and re-estimated the model using system GMM. **The** coefficient on DFII remained positive and statistically significant, though the magnitude of the effect decreased slightly. This suggests that pioneers drive part of the effect, yet the relationship exists across the broader sample of SSA countries.

Still, we deemed it fit to continue to ensure the inexistence of a distorting factor with the unprecedented economic disruption of the COVID-19 pandemic. Therefore, our baseline model was estimated with a dummy variable that took the value of 1 for the years 2020 and 2021 and was 0 otherwise. The DFII coefficient remained positive and statistically significant at the 1% level (β = 0.148, p-value = 0.003), whilst the COVID-19 variable was negative and significant, as anticipated. This, in turn, confirms that the positive causal relationship between DFI and economic growth was not a pandemic period artifact but rather a structural one prevailing over time.

Economic Interpretation and Channels of Transmission

The statistically meaningful coefficient estimates of 0.154 for the digital inclusion index offers substantial empirical validation for the theoretical mechanisms outlined earlier. Robust, positive, and significant in nature, the coefficient on DFII provides a strong empirical underpinning to the theoretical channels developed in Section 2.1. Digital financial services support African growth through several interconnected mechanisms. Capital Accumulation through Increased Mobilization of Savings: Digital wallets and mobile money accounts greatly minimize the formal saving barriers. Saving small amounts through digital methods provides convenience, security, and low cost, thus discouraging households and small businesses from keeping their savings in informal, less productive instruments (such as cash or livestock) and eventually pushing them into the formal financial system.

This analysis identifies several transmission channels through which the impact of DFI materializes on macroeconomic growth, aligning with classical and endogenous growth theories, Transmission Channels for Economic Growth: Capital Mobilization and Savings Augmentation: DFI significantly capitalizes on vast reserves of dormant capital, thereby elevating the overall national savings rate and augmenting the volume of loanable funds available for investment in the formal economy, Improvement in Capital Allocation Efficiency: Perhaps the most pivotal channel, DFI mitigates information asymmetries through the digital data trails generated by transactions.

This mechanism enables financial institutions to conduct superior creditworthiness assessments, directing capital more precisely towards productive, investment-worthy purposes, particularly benefiting otherwise excluded SMEs and entrepreneurs, Productivity Enhancement through Reduced Friction: Beyond lowering basic transaction costs, digital payments minimize the time and resources merchants expend on cash handling and management. This liberated capacity is reallocated to core value-adding activities, streamlining operations, facilitating swift supply chain payments, and ensuring prompt payroll management, Promotion of Economic Formalization: DFI acts as a profound structural mechanism that channels a substantial portion of the informal economy into a digitally traceable domain. By shifting transactions from untraceable cash to measured digital systems, it refines the accuracy of national accounts and effectively broadens the tax base for governments (Sahay et al., 2020), Risk Management and Consumption Smoothing: From the perspective of households and firms, digital financial instruments (e.g., remittances and savings products) empower them to absorb economic shocks (such as job loss or drought). This ability stabilizes aggregate demand and safeguards the depletion of human capital during economic downturns.

The finding of a significant coefficient for DFI conforms with micro-level studies documenting its linkage to improved savings mobilization (Batista & Vicente, 2020) and enhanced credit allocation through reduced information asymmetry (Berg et al., 2020). Future research employing household or firm-level data would be instrumental in formally testing these hypothesized mediating channels—specifically savings mobilization and access to credit—between DFI and aggregate growth.

SUMMARY OF FINDINGS

This analysis provides rigorous empirical examination of the causal impact of digital financial inclusion on economic expansion in Sub-Saharan Africa. The study began by developing a detailed multidimensional digital financial inclusion index, comprehensively measuring access, usage, and quality aspects. To address the pervasive issue of endogeneity, the two-step System Generalized Method of Moments (System GMM) estimator was deployed, which conclusively revealed a positive and statistically significant causal relationship. Specifically, a one standard deviation increase in the DFII corresponds to an annual rise in the GDP per capita growth rate of 0.154 percentage points. This effect is significant both statistically and economically, as it accounts for approximately 7.9 percent of the average annual per capita growth rate realized in the sample of 35 SSA countries between 2004 and 2022. These key findings were consistently sustained across multiple robustness checks, including altering the instrument set, removing regional outliers, and controlling for the structural break imposed by the COVID-19 pandemic.

Furthermore, the analysis confirmed the persistence of economic growth in the region, evidenced by the significant coefficient of the lagged dependent variable. Control variables largely aligned with theoretical predictions: investment, trade openness, and human capital exhibited positive relationships with growth, while government consumption and inflation showed negative correlations.

In summation, the findings present strong evidence favoring the proposition that DFI is a major and reliable driver of economic growth in Sub-Saharan Africa. The use of a comprehensive DFI measure and a powerful identification strategy that effectively handles reverse causality and unobserved heterogeneity rightfully elevates the study beyond the mere correlational evidence presented by previous research. These definitive results thus equip policymakers with the evidence required to support promising DFI programs as a critical pillar toward achieving sustainable regional economic development.

Policy Implications

The established causal relationship requires development of specific, actionable policy guidance for governments, central banks, and development institutions across the region. Policy suggestions organize around three principal strategic areas.

Strategic Public Capital Allocation for Foundational Infrastructure

Governments, in conjunction with private sector stakeholders, must recognize core digital public goods as critical public infrastructure. This includes robust national broadband networks, reliable electricity grids, and sovereign digital identity systems (Foundational IDs).

Targeted investment that explicitly addresses the urban-rural disparity is paramount. Specifically, a robust national digital ID system can substantially lower Know-Your-Customer (KYC) compliance costs for financial institutions, thereby facilitating the secure and efficient onboarding of millions of currently underserved customers.

Cultivating an Enabling and Trustworthy Regulatory Framework

Since the quality dimension of DFI is a key determinant of growth, policy must prioritize building digital trust. This entails establishing stringent cybersecurity infrastructure, comprehensive data-protection standards, and clear, risk-based regulations. Mandate Interoperability: Regulators should enforce or strongly incentivize interoperability among all major payment platforms (e.g., mobile money, bank, and FinTech systems).

This is critical for maximizing network effects and ensuring user convenience by creating a unified national payments system, Promote Innovation via Sandboxes: The creation of formal regulatory sandboxes allows FinTechs and financial institutions to test novel products under controlled environments, often with a temporary relaxation of existing rules.

This mechanism ensures an effective calibration of the trade-off between fostering innovation and safeguarding consumer protection, Proportional AML/CFT Rules: The application of Anti-Money Laundering/Combating the Financing of Terrorism (AML/CFT) rules must be risk-based and proportional to transaction size. This approach avoids imposing unnecessary compliance burdens that could exclude low-income users from the formal financial system.

Fostering Demand-Side Capacity and Market Contestability

Supply-side investments must be synchronized with strategic efforts to build demand-side capacity and ensure a competitive market environment, Targeted Digital and Financial Literacy: National literacy initiatives should transition from mere awareness campaigns to the actual building of practical skills. Curricula must emphasize comparing transaction costs, comprehending the terms of digital credit and savings products, and understanding self-protection against fraud and over-indebtedness.

Such programs are essential for translating DFI adoption into safe and productive use, particularly for vulnerable groups, Enhance Market Contestability: Policymakers should actively cultivate a competitive environment by adopting licensing regimes that reduce barriers to entry for non-bank players (FinTechs and Mobile Network Operators). Furthermore, ensuring transparent and equitable access to vital public infrastructure, such as national payment switches and credit bureaus, is necessary to curb anti-competitive practices, thereby driving innovation, improving service quality, and lowering costs for end-users.

Limitations and Avenues for Future Research

Avenues for Future Research

While this study establishes a definitive causal link at the aggregate macroeconomic level, several crucial avenues remain open for future inquiry. Firstly, research should shift focus to distributional outcomes, utilizing household- or firm-level microdata to investigate how the welfare gains from DFI are stratified across socio-economic groups. This involves assessing its impact on mitigating income inequality, the gender gap, and the urban-rural divide.

Secondly, there is a clear need for channel-specific analysis: as more granular data becomes available, researchers should isolate the unique contributions of distinct DFI services—such as payments, savings, and credit products—to overall economic expansion.

Thirdly, the macroeconomic context warrants exploration; specifically, investigating whether the efficacy of DFI is mediated by the broader institutional environment, including the rule of law and inflation stability. Fourthly, given that our analysis covered a period of intensive adoption, future work must focus on the long-term growth effects as SSA digital financial markets achieve maturity.

Finally, two methodological refinements are essential: Future research would benefit significantly from the deployment of finer proxies for human capital that specifically capture digital literacy—the actual prerequisite skill for effective DFI engagement—rather than relying on noisy standard education indices. Furthermore, while this study theorizes the transmission channels, subsequent research should harness micro-level data to empirically test these mechanisms (e.g., savings mobilization versus credit allocation) using advanced mediation analysis techniques.

While acknowledging that Digital Financial Inclusion (DFI) does not represent a panacea for all structural challenges, the empirical findings of this study conclusively establish its role as a powerful and necessary catalyst for economic growth in Sub-Saharan Africa.

The foremost policy imperative arising from this research is the need for concerted, multi-stakeholder collaboration to architect and sustain truly inclusive digital financial ecosystems. Such systems are indispensable for dismantling persistent historical constraints and initiating a new, sustainable wave of broad-based economic expansion across the continent.

Furthermore, although this analysis focused specifically on Sub-Saharan Africa, the advanced methodological framework—encompassing the rigorous construction of a composite, multidimensional DFI index and the stringent identification strategies used for causal inference—is highly generalizable. This robust structure can be readily adapted and applied to empirically assess the impact of digital financial inclusion in any developing market experiencing comparable financial development deficiencies.

To broaden the scope of this research, future studies could replicate this analysis in other developing regions. Such expansion would enable valuable cross-regional comparisons and help generalize digital financial inclusion policy frameworks, particularly in understanding growth effects during periods of rapid DFI adoption similar to the SSA experience. When these markets mature, an analysis on the persistence of this effect in the long-run, and any potential effect occurring in stages (e.g. saturation, waves of innovation), will constitute the focus of utmost attention.

Funding: This work was supported and funded by the Deanship of Scientific Research at Imam Mohammad Ibn Saud Islamic University (IMSIU) (grant number IMSIU-DDRSP2501).

REFERENCES

Aghion, P., & Howitt, P. (2009). The economics of growth. MIT Press.

Batista, C., & Vicente, P. C. (2020). Improving access to savings through mobile money: Experimental evidence from African smallholder farmers. World Development, 129, 104905. https://doi.org/10.1016/j.worlddev.2019.104905

Beck, T., & Cull, R. (2023). Financial inclusion in Africa. In F. Cheru, C. Cramer, & A. Oqubay (Eds.), The Oxford handbook of the Ethiopian economy (pp. 567-586). Oxford University Press.

Berg, T., Burg, V., Gombović, A., & Puri, M. (2020). On the rise of fintechs: Credit scoring using digital footprints. The Review of Financial Studies, 33(7), 2845-2897. https://doi.org/10.1093/rfs/hhz099

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. Journal of Econometrics, 87(1), 115-143. https://doi.org/10.1016/S0304-4076(98)00009-8

Demirgüç-Kunt, A., Klapper, L., Singer, D., Ansar, S., & Hess, J. (2018). The Global Findex Database 2017: Measuring financial inclusion and the fintech revolution. The World Bank. https://doi.org/10.1596/978-1-4648-1259-0

Della Peruta, M. (2018). Adoption of mobile money and financial inclusion: A macroeconomic approach through cluster analysis. Economics of Innovation and New Technology, 27(2), 154-173. https://doi.org/10.1080/10438599.2017.1310792

Evans, O., & Adeoye, B. (2020). Digital finance: A powerful tool for financial inclusion in Africa. Journal of Banking and Financial Economics, 2(12), 1-18. https://doi.org/10.7172/2353-6845.jbfe.2020.2.1

Gomber, P., Kauffman, R. J., Parker, C., & Weber, B. W. (2018). On the fintech revolution: Interpreting the forces of innovation, disruption, and transformation in financial services. Journal of Management Information Systems, 35(1), 220-265. https://doi.org/10.1080/07421222.2018.1440766

GSMA. (2023). State of the industry report on mobile money 2023. GSM Association. https://www.gsma.com/mobilefordevelopment/wp-content/uploads/2023/03/State-of-the-Industry-Report-on-Mobile-Money-2023.pdf

Jack, W., & Suri, T. (2011). Mobile money: The economics of M-PESA (NBER Working Paper No. 16721). National Bureau of Economic Research. https://www.nber.org/papers/w16721

Kim, D.-W., Yu, J.-S., & Hassan, M. K. (2018). Financial inclusion and economic growth in OIC countries. Research in International Business and Finance, 43, 1-14. https://doi.org/10.1016/j.ribaf.2017.07.178

Levine, R. (2005). Finance and growth: Theory and evidence. In P. Aghion & S. N. Durlauf (Eds.), Handbook of economic growth (Vol. 1, pp. 865-934). Elsevier. https://doi.org/10.1016/S1574-0684(05)01012-9

McKinnon, R. I. (1973). Money and capital in economic development. Brookings Institution Press.

Ozili, P. K. (2021). Digital finance, green finance and social finance: Is there a link? Financial Internet Quarterly, 17(1), 1-7. https://doi.org/10.2478/fiqf-2021-0012

Roodman, D. (2009). How to do xtabond2: An introduction to difference and system GMM in Stata. The Stata Journal, 9(1), 86-136. https://doi.org/10.1177/1536867X0900900106

Romer, P. M. (1990). Endogenous technological change. Journal of Political Economy, 98(5), S71-S102. https://doi.org/10.1086/261725

Sahay, R., von Allmen, U. E., Lahreche, A., Khera, P., Ogawa, S., Bazarbash, M., & Beaton, K. (2020). The promise of fintech: Financial inclusion in the post COVID-19 era (IMF Departmental Paper No. 2020/009). International Monetary Fund. https://doi.org/10.5089/978151356873.006

Schumpeter, J. A. (1934). The theory of economic development: An inquiry into profits, capital, credit, interest, and the business cycle. Harvard University Press.

Shaw, E. S. (1973). Financial deepening in economic development. Oxford University Press.

Suri, T., & Jack, W. (2016). The long-run poverty and gender impacts of mobile money. Science, 354(6317), 1288-1292. https://doi.org/10.1126/science.aah5300

Tchamyou, V. S. (2019). The role of information sharing in modulating the effect of financial access on inequality. Journal of African Business, 20(3), 317-338. https://doi.org/10.1080/15228916.2019.1582294

Tchamyou, V. S., Erreygers, G., & Cassimon, D. (2019). Inequality, ICT and financial access in Africa. Technological Forecasting and Social Change, 139, 169-184. https://doi.org/10.1016/j.techfore.2018.11.004 .

