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Information and Communication Technology (ICT) Diffusion and Economic Growth in Sub-Saharan Africa: Evidence from Dynamic System GMM Estimation

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ABSTRACT

This study investigates the heterogeneous impacts of information and communication technology (ICT) diffusion on economic growth across all 48 Sub-Saharan African (SSA) countries from 2002 to 2023. Employing the Two-Step System Generalized Method of Moments (System GMM) to address endogeneity, dynamic persistence, and unobserved heterogeneity, the study simultaneously examine four distinct ICT indicators: mobile cellular subscriptions, internet usage, fixed broadband subscriptions, and fixed-line telephone subscriptions. Results reveal sharply divergent effects: mobile subscriptions and fixed broadband significantly boost GDP per capita, underscoring their roles as catalysts for financial inclusion and structural transformation. In contrast, internet usage exhibits a robustly negative effect, suggesting that unstructured digital access without complementary investments in digital literacy, institutional quality, or regulatory frameworks may impede growth. Fixed-line telephony also shows a significant negative association reflecting its technological obsolescence in SSA's mobile-leapfrogged landscape. Diagnostic tests confirm the validity and stability of our preferred specification. These findings challenge the notion of ICT as a monolithic growth engine and highlight that developmental returns are contingent on technology type and enabling conditions. The study offers actionable policy guidance for maximizing the growth dividends of digital transformation in SSA.

Keywords: ICT Diffusion, Economic Growth, System GMM, Sub-Saharan Africa, Digital Infrastructure

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1. Introduction

1.1. Background of the Study

The relationship between ICT diffusion and economic growth has become a key area of study in development economics, particularly in the context of Sub-Saharan Africa (SSA), where digital transformation is increasingly recognized as a catalyst for structural change, productivity gains, and inclusive development. The theoretical underpinning of this relationship is endogenous growth theory (Romer, 1990; Lucas, 1988). It claims that one of the main drivers of long-term economic growth is technological advancement, as reflected in ICT infrastructure. ICTs lower transaction costs, improve market efficiency, facilitate knowledge spillovers, and increase the accumulation of human capital, all of which promote innovation and productivity gains across sectors (Waverman, et al. 2005; Röller & Waverman, 2001). ICTs may act as a "leapfrogging" mechanism, allowing nations to avoid intermediate stages of technological development in developing economies where institutional and infrastructural limitations frequently obstruct traditional growth channels (Donner & Escobari, 2010).

Empirical research on the nexus between ICT and growth in SSA has produced erratic and situation-specific findings. Recent research highlights the importance of threshold effects, institutional quality, and complementary factors like access to electricity and human capital. For instance, if more than 60% of the population has access to electricity, Kouam & Asongu, (2023) demonstrate a U-shaped, non-linear relationship between fixed broadband penetration and economic growth. However, below this threshold, growth due to broadband expansion may even be impeded by infrastructure bottlenecks. In a similar vein, Abdulqadir & Asongu, (2022) , discover that ICT, particularly when paired with strong regulatory frameworks, has a positive asymmetric influence on growth above a critical internet penetration threshold of 3.55%. These results highlight the fact that the sheer spread of ICT does not always result in economic growth; rather, enabling environments mediate its effectiveness.

Mixed effects of ICT indicators are highlighted by other studies. A 10% increase in mobile phone penetration raises GDP per capita by 1.2%, claim (Donner & Escobari, 2010). In line with earlier research by Chavula, (2013), Haftu, (2019) shows that internet penetration is still statistically insignificant, despite the fact that mobile phone penetration significantly spurs growth. However, Simione & Li, (2021) show that broadband penetration increases GDP per capita growth by 0.37 percentage points for every percentage point increase using instrumental variable approaches (submarine cable landings). It also shifts employment toward services, especially for women, and raises total factor productivity (TFP) by 1.5%. These discrepancies suggest that the choice of the ICT proxy, estimate method, and sample composition have a substantial influence on the outcomes.

In order to handle endogeneity, reverse causality, and unobserved heterogeneity, dynamic panel techniquesin particular, the System Generalized Method of Moments (System GMM) have become more and more popular in recent literature. System GMM is used to extract causal effects in studies like Haftu, (2019), Solomon & Van Klyton, (2020), and Myovella et al., (2021). However, these studies frequently concentrate on subsets of SSA countries (e.g., 27–39 nations) or time periods (e.g., pre-2020) and lacks clarity on model selection, stability and robustness. Furthermore, a lot of analyses overlooked important controls like institutional quality (GE), domestic credit to private sector (DCPS), or gross fixed capital formation (GFCF), which are known to interact with digital infrastructure to shape growth trajectories, or they treat ICT indicators in isolation (Dossou et al., 2024; Correa & Esquivias, 2025).

Despite these advances, significant methodological and empirical gaps remain. First, there is currently no study that fully examines all four of the main ICT indicators simultaneously in a single System GMM framework for the entire group of 48 SSA countries: internet usage, fixed broadband per 100 people, mobile subscriptions per 100 people, and fixed-line telephony per 100 people. Second, in some studies, the stability, robustness, and model selection criteria were not clearly shown (Haftu, 2019). Third, despite its recognition as a moderator, institutional quality (Government effectiveness) is not always included as a controlled variable alongside gross fixed capital formation (GFCF) and domestic credit to private sector (DCPS).

These gaps are directly addressed by this study. Using a contemporary panel dataset that includes all 48 SSA countries from 2002 to 2023, the study employs System GMM to thoroughly estimate the disparate effects of several ICT diffusion indicators on economic growth. This study clearly shows the model selection criteria, stability, and robustness tests while adjusting for GFCF, DCPS, and government effectiveness. In the process, the study provide the most comprehensive geographical and temporal analysis to date and illuminate the conditions under which specific ICT channels either facilitate or impede economic growth in Sub-Saharan Africa. By coordinating ICT diffusion with complementary governance, capital formation, and financial changes, our research seeks to inform the development of policies that maximize growth rewards.

1.2. Hypotheses

The theoretical expectation that ICT diffusion promotes economic growth is well-established in endogenous growth models, which emphasize technology as a non-rival input that increases productivity and knowledge spill overs. However, empirical studies conducted in Sub-Saharan Africa (SSA) have shown that the growth impact of ICT is neither constant nor automatic; rather, it varies significantly depending on the type of technology and is highly reliant on the condition of infrastructure, human capital, and institutions. This study formulates the following hypothesis in light of this complex evidence.

- H_1: Mobile phone subscriptions have a statistically significant effect on economic growth in SSA countries.
- H_2: Internet usage (as a share of the population) has statistically significant effect on economic growth in SSA countries.
- H_3: Fixed broadband subscriptions have a statistically significant effect on economic growth in SSA countries.
- H_4: Fixed-line telephone subscriptions have a statistically significant effect on economic growth in SSA countries.

2. Theoretical and Empirical Literatures Reviews

2.1. Theoretical Literature Reviews

The nexus between information and communication technology (ICT) diffusion and economic growth is fundamentally based on endogenous growth theory, which challenges the exogenous treatment of technological advancement in neoclassical models. This theory, which was developed by Romer (1990) and Lucas (1988), holds that long-term economic progress is driven by internal forces, specifically investments in knowledge, human capital, and innovation. According to this paradigm, ICT infrastructure is not merely a tool for increasing efficiency but rather a non-rival, partially excludable input that generates increasing returns to scale and positive externalities across the economy. By lowering transaction costs, enhancing market transparency, and accelerating the dissemination of knowledge, ICT serves as a catalyst for structural change and productivity gains (Waverman,et al, 2005; Röller & Waverman, 2001).

One of the main ways ICT fosters growth is through knowledge spillovers. In contrast to physical capital, digital technology makes it possible for information to be shared almost instantly across borders, industries, and businesses. In poor countries with limited traditional R&D capabilities, this improves allocative efficiency, reduces information asymmetries, and fosters innovation ecosystems (Donner & Escobari, 2010). ICT offers a potential "leapfrogging" path in Sub-Saharan Africa (SSA), where infrastructure and institutional shortcomings can occasionally impede traditional growth paths. Mobile money platforms, like M-Pesa in Kenya, have enhanced financial inclusion and entrepreneurship by obviating the necessity for significant banking infrastructure (Suri & Jack, 2016).

However, the theoretical expectation of a uniformly favourable ICT–growth link is limited by complementarity criteria, which are emphasized in more recent extensions of endogenous growth models. According to Acemoglu & Restrepo, (2018), the productivity impact of new technologies depends on the availability of complementary inputs like skilled labor, reliable infrastructure (like power), and flexible institutions. Their idea is that if technology is implemented without these enablers, it could lead to "so-so automation" that substitute’s labour without boosting output. This insight is particularly relevant for SSA, where digital infrastructure usually outpaces institutional readiness or human capital development.

The institutional economics perspective, which stresses how property rights, legal frameworks, and the caliber of governance influence the returns on technology investment, is in line with this conditional view. According to North, (1990), institutions set the "rules of the game" that determine whether technological advancement promotes inclusive growth or exacerbates inequality and rent-seeking. Ineffective digital activities (like using social media without any economic connections) or elites may be the main beneficiaries of ICT expansion in weak institutional frameworks, which would reduce or even reverse its growth effects (Byanyima et al., 2025). However, by fostering competitive markets, protecting intellectual property, and ensuring secure online transactions, good institutions can increase ICT's growth potential (Abdulqadir & Asongu, 2022; Dossou et al., 2024).

Additionally, the Schumpeterian concept of creative destruction provides a dynamic lens for understanding the sectoral implications of ICT. Innovation powered by ICT upends established industries and creates new ones by redistributing capital and labor toward more fruitful uses. Simione and Li, (2021), document this structural shift in SSA, demonstrating that the expansion of broadband increases employment in services, particularly for women, while decreasing dependence on low-productivity agriculture. These reallocation benefits are essential for long-term growth, but their full realization requires adjusting social policies and labor markets.

Finally, the threshold effects observed empirically in SSA are theoretically supported by big push theories and nonlinear growth models (Kouam & Asongu, 2023; Abdulqadir & Asongu, 2022). They suggest that until a critical mass of auxiliary resources, like network density, digital literacy, or power coverage, is attained, ICT investments may not yield a profit. Under this threshold, fixed costs take precedence, and digital infrastructure may continue to be misallocated or underutilized, which would have negative or insignificant effects on growth.

In summary, endogenous growth theory presents a strong qualitative case for a positive ICT–growth relationship; however, its practical implementation in SSA is contingent upon several interconnected factors, such as institutional quality, infrastructure readiness, human capital, and policy coherence. The need for empirical models that exactly the approach taken in this study not only take into consideration the direct effects of a number of ICT indicators but also dynamically interact with significant macroeconomic and institutional factors is supported by this theoretical complexity.

2.2. Empirical Literature Review

The impact of ICT diffusion on economic growth has been the subject of an increasing amount of empirical research in Sub-Saharan Africa (SSA); however, results remain inconsistent because of differences in ICT proxies, estimate methods, sample size, and the inclusion of contextual modifiers. The data on the four primary ICT indicators mobile subscriptions, internet usage, fixed broadband, and fixed-line telephony are examined in this section using new panel studies that take endogeneity and dynamic feedback into account using advanced econometric techniques.

Mobile phone penetration is the ICT factor that continuously accelerates growth in SSA. Using system GMM on a panel of African countries (2000–2021), Dah et al. (2025) found that a 10% increase in mobile subscribers increases GDP per capita by 1.2%. Human capital increases the effects. Similar to this, Haftu (2019) and Chavula (2013), show that mobile telephony has a significant positive impact on growth and living standards, even in situations where internet usage is minimal. Mobile money systems, like M-Pesa, show how mobile technology is accessible, affordable, and quickly scalable, which explains why it has significantly improved financial inclusion, market efficiency, and entrepreneurial activity in Sub-Saharan Africa (Suri & Jack, 2016). According to Myovella et al. (2020), mobile subscriptions have a greater growth impact in SSA than in OECD nations, highlighting their developmental significance in environments with limited infrastructure.

However, the real data on internet usage is highly variable and environment-specific. Asongu and Abdulqadir (2021) discover that, above a critical threshold of 3.55% internet penetration, regulatory quality plays a critical role in amplifying the favorable asymmetry effect. According to Nsavyimana & Li (2025), who focus on East Africa (2007–2021), there is a significant long-term elasticity of +14.51 and a short-term effect of +0.35% in log GDP per capita for every 1% increase in internet users. Manas Tripathi et al. (2016) also find a cointegrated long-term positive connection across 42 SSA countries (1998–2014), but the short-term effects are negative, suggesting adjustment lags. Additionally, Dossou et al, (2024) note that in democratic regimes, where entrepreneurship and transparency are more active, the growth impact of the internet (when paired with mobile) is noticeably stronger.

Other research, however, reveals negative results or even no effects at all. Although internet penetration is statistically insignificant, mobile phones have a significant impact on GDP per capita growth (Haftu, 2019; Chavula, 2013). Using simultaneous equations (3SLS) on 27 SSA countries (2008–2019), Byanyima et al., (2025) report a negative direct coefficient of –0.048 for internet usage per capita on growth, which is the most noteworthy finding. They caution that without robust institutions, greater internet access might not lead to profitable economic activity. These variations show that internet dispersion alone is not enough to generate the growth dividend of the internet, and that it depends on several additional factors, such as digital literacy, energy access, and institutional quality (Correa & Esquivias, 2025).

The characteristics of fixed broadband subscriptions are obviously non-linear. Applying panel smooth transition regression (PSTR) and GMM to 33 African nations between 2010 and 2020, Kouam & Asongu, (2023), demonstrate a U-shaped relationship contingent on electricity coverage: a 1% increase in broadband slows growth by 2.58% below a 60% population threshold and accelerates growth by 2.43% above it. This demonstrates the dangers of making "premature" digital investments in nations with low electricity levels. In 33 SSA countries (2005–2017), Simione and Li, (2021), found that a 1 percentage point increase in broadband penetration boosts GDP per capital growth by 0.37 percentage points; increases total factor productivity by 1.5%, and shifts employment toward services, particularly for women. This shows that broadband does yield significant benefits when infrastructure conditions are favourable. Using System GMM, Myovella et al. (2020) confirm a favorable, albeit smaller, effect in SSA. On the other hand, Minges (2016) reinforces the threshold narrative by pointing out that fixed broadband frequently exhibits negligible or adverse effects in early-stage digital economies in a meta-analysis that includes SSA cases like Senegal.

Fixed-line phone users, once a key component of telecom expansion, are now mainly inconsequential in SSA. According to Chavula, (2013), the conclusion that fixed lines have a positive effect on living standards in Africa between 1990 and 2007 is mainly historical; more recent research either disregards fixed lines or considers them to be out of date. Due to the nearly universal decline in fixed-line usage in SSA in favour of mobile alternatives, fixed-line's independent contribution to the current dynamics of growth is either negligible or negative, reflecting sunk costs in outdated infrastructure.

The literature has moved toward dynamic panel approaches, such as System GMM, to address endogeneity, reverse causation, and unobserved heterogeneity (Haftu, 2019, Solomon & Van Klyton, 2020, and Myovella et al., 2021). Instrumental variable approaches (Simione & Li, 2021; Hjort & Poulsen, 2019) further strengthen causal identification. However, there are still significant limitations: (1) most studies only examine 27–42 SSA countries, excluding smaller or less data-rich nations; (2) few cover the entire post-2020 period, omitting recent digital acceleration; (3) many examine ICT indicators separately rather than collectively; and (4) some studies lack clarity regarding stability, robustness, and model selection criteria (Haftu, 2019), and (5) the unequal inclusion of crucial controls like government effectiveness, domestic credit to private sector, and GFCF (Dossou et al., 2024; Ebou Correa & Esquivias, 2025).

2.3. Conceptual Framework

The study's conceptual underpinnings are derived from institutional economics, complementarity theory, and endogenous growth theory. According to GDP per capita, it implies that the proliferation of ICT, as measured by internet usage, fixed broadband per 100 people, mobile subscription per 100 people, and fixed-line telephone per 100 people, affects the economic growth of Sub-Saharan Africa. Enabling factors such as macroeconomic openness, the financial inclusion (DCPS), infrastructure (gross fixed capital formation), and institutional quality (government effectiveness) are necessary for the impact to occur. By serving as amplifiers and thresholds, they influence how effective ICT diffusion is. Without them, ICT may be of little or no use, but when it is, it fosters productivity, inclusive growth, and structural transformation.

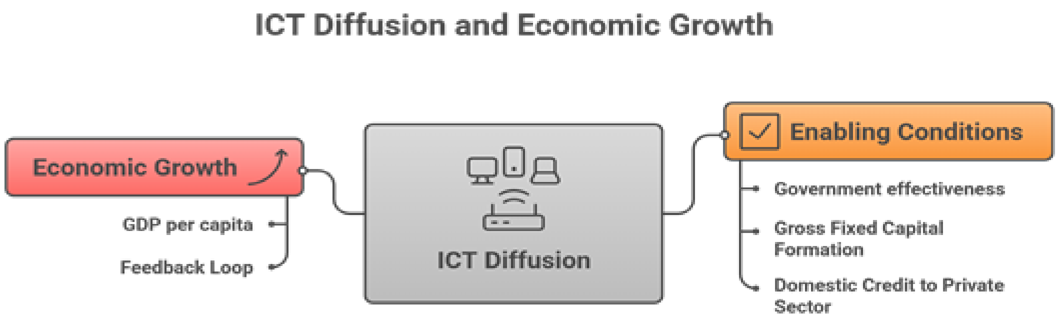

Figure 1: ICT diffusion and economic growth

Source: author's own illustration 2025

3. Research Methodology

3.1. Research Design and Scope

This study employs a dynamic panel research approach to examine the relationship between economic growth and information and communication technology (ICT) diffusion in Sub-Saharan Africa (SSA). The study's comprehensive temporal and spatial coverage, which spans 48 SSA countries from 2002 to 2023, improves the reliability and generalizability of the results. A panel structure is particularly appropriate because static cross-sectional or single-country approaches cannot capture the cross-country variation and temporal dynamics in ICT adoption. Furthermore, the dataset satisfies the criteria for a Small T, Large N panel (48 countries over 22 years), which is an environment in which the System Generalized Method of Moments (System GMM) performs especially well (Roodman, 2009). This estimator enables robust handling of unobserved heterogeneity, simultaneity bias, and reverse causality between ICT and economic growth. The design, which is based on the endogenous growth theory, emphasizes ICT as a non-rival input that fosters knowledge spillovers, productivity gains, and structural transformation while also acknowledging the importance of complementary components like institutions and capital investment.

3.2. Data and Variables

This study only uses secondary data from the World Bank's World Development Indicators (WDI), which provide reliable, comparable, and widely used metrics across SSA countries. The dependent variable, economic growth, is proxied by real GDP per capita (constant US$), a popular measure that takes into consideration both macroeconomic success and improvements in living standards.

Four distinct proxies are used by the independent variables to measure ICT diffusion: internet usage (as a percentage of the population), mobile cellular subscriptions per 100 people, fixed broadband subscriptions per 100 people, and fixed-line telephone subscriptions per 100 people. The disadvantages of relying solely on one proxy are mitigated and the complex nature of ICT development is recognized by employing a range of indicators.

The analysis incorporates three control variables to account for enabling factors that influence the relationship between ICT and growth. First is government quality represented by the World Bank's governance indicators, which incorporate six elements: this study uses government effectiveness as a proxies . It takes strong institutions to turn ICT adoption into long-term economic benefits. Second, Domestic credit to private sector (DCPS) refers to financial resources provided to the private sector by financial corporations, such as through loans, purchases of nonequity securities, and trade credits and other accounts receivable, that establish a claim for repayment (World Bank, 2025). Third, gross fixed capital formation (GFCF as a percentage of GDP) is included as a measure of capital accumulation and infrastructure, both of which are essential for effectively leveraging ICT.

3.3. Model Specification

The study starts with a standard static panel regression to estimate the effect of ICT diffusion on economic growth in Sub-Saharan Africa. By using increasingly complex estimators, the studygradually address the main econometric challenges of endogeneity of ICT variables, unobserved country-specific effects, and dynamic feedback. The methodological development is made clearer by this step-by-step approach, which also supports our selection of the System Generalized Method of Moments (System GMM) as the benchmark specification.

Table 1: Variable Definition Table

Variable Name	Symbol	Definition	Measurement Unit	Data Source (WDI Code)	Expected Sign
GDP per capita	GDPPC	Gross Domestic Product per capita (constant prices), proxy for economic growth	Current US$	World Development Indicators (NE.TRD.GNFS.ZS)	—
Lagged GDP per capita	GDPPC(-1)	One-period lag of GDP per capita capturing income persistence	Current US$	Computed from WDI	+
Mobile Cellular Subscriptions	MCSP100	Number of mobile cellular subscriptions per 100 people	Subscriptions per 100 people	WDI (IT.NET.BBND.P2)	+
Fixed Broadband Subscriptions	FBBSP100	Fixed broadband subscriptions per 100 people	Subscriptions per 100 people	WDI (VA.EST)	+ (conditional)
Internet Usage	IUI	Individuals using the internet (% of population)	Percentage (%)	WDI (EG.ELC.ACCS.ZS)	± (ambiguous)
Fixed Telephone Subscriptions	FTSP100	Fixed-line telephone subscriptions per 100 people	Subscriptions per 100 people	WDI (RQ.EST)	−

3.3.1. Baseline Static Panel Model

The starting point is a static fixed-effects (FE) or random-effects (RE) model:

$$\text{GDPpc\_it} = \alpha + \beta 1\text{ICT\_it} + \gamma \text{Xit} + \mu\text{i} + \lambda\text{t} + \epsilon\text{i}$$

Where, GDPpc_it is GDP per capita in country i at time t, ICT_it represents one of four ICT indicators (mobile, internet, fixed broadband, fixed-line), X_it is a vector of control variables (DCPS, GFCF, GE), μ_i denotes country fixed effects, λ_t captures time fixed effects, and ϵ_i is the idiosyncratic error.

This model has three major problems even though it takes time-invariant variability into account.First, it ignores dynamic adjustment because economic growth is inherently persistent and the exclusion of lagged GDP introduces omitted variable bias (Nickell,1981). Second, ICT variables are most likely endogenous simultaneity (growth allows ICT investment), and OLS/FE estimates may be distorted by measurement error. Third, in short panels ($T < 20$), FE estimators are inefficient and susceptible to attenuation bias.

3.3.2. First-Differenced GMM (Difference GMM)

The study uses the Difference GMM estimator Arellano & Bond, (1991), and adds dynamics by including a lagged dependent variable to address persistence and unobserved heterogeneity:

$$\Delta \text{GDPpc}_{\text{it}} = \rho \Delta \text{GDPpc}_{\text{i(t}-1)} + \beta 1 \Delta \text{ICT\_it} + \gamma \Delta \text{Xit} + \Delta \epsilon\text{i}$$

Here, first-differencing eliminates μ_i, and lagged levels of all endogenous variables (e.g., ICTi(t-2), ICT_i(t-3),….) serve as instruments for their differenced counterparts. This approach effectively tackles unobserved fixed effects and endogeneity under the assumption that instruments are valid (i.e., uncorrelated with errors).

Nonetheless, Difference GMM has well-established drawbacks for panels with persistent series, which are common in growth data. When the dependent variable is significantly auto-correlated, lag levels become inadequate tools for first differences, leading to low precision and a notable finite-sample bias (Blundell & Bond, 1998). This is particularly troublesome for ICT variables, which have a slow evolution and a high serial correlation.

3.3.3. System GMM: The Preferred Specification

To overcome the limitations of Difference GMM, the study employs the System GMM estimator (Blundell & Bond, 1998), which combines moment conditions from the first-differenced equation (instrumented with delayed levels) and the levels equation (instrumented with lagged differences). The system is:

$$\Delta GDPpc_{it} = \rho \Delta GDPpc_{i(t-1)} + \beta 1 \Delta ICT\_it + \gamma \Delta Xit + \Delta \epsilon i$$
$$GDPpc_{it} = \rho GDPpc_{i(t-1)} + \beta 1 ICT_{it} + \gamma Xit + \mu i + \epsilon i$$

System GMM improves efficiency and reduces bias by exploiting additional orthogonality conditions. It is especially effective when the series is persistent (i.e., ρ close to 1), as is typical in per capita income data. (Roodman, 2009), demonstrates that System GMM yields more reliable estimates than Difference GMM in panels with moderate T (10–30) and N > T conditions that match our dataset (N = 48, T = 22).

For estimating dynamic panel models of the relationship between ICT and growth in Sub-Saharan Africa, System GMM offers several significant advantages. First, it offers trustworthy estimates in spite of endogenous regressors and unobserved country-specific heterogeneity, two frequent issues in growth empirical research. Second, as is common with macroeconomic panel data, it performs better than other estimators when the dependent variable (like GDP per capita) exhibits strong persistence. Even if our model only employs time-varying controls (DCPS, GFCF, and GE), System GMM's system structure theoretically permits the indirect identification of time-invariant variables. However, fulfilling significant econometric assumptions is necessary for valid inference. Consequently, the studyconduct conventional diagnostic tests: the absence of second-order serial correlation in the first-differenced residuals (AR(2) test) ensures instrument validity, and the Hansen test of over-identifying limits establishes whether our instruments are exogenous. The study follows Roodman's (2009) recommendation to minimize the risk of instrument proliferation, which can lower the power of the Hansen test and bias estimates, by collapsing the instrument matrix and restricting instruments to lags t–2 and t–3. Following best practices (Bond,2002;Roodman,2009), the study provide one-step estimates (efficient under homoskedasticity) and two-step estimates with (Windmeijer, 2005), corrected standard errors to account for finite-sample bias in the latter.

3.3.4. Final Empirical Specification

Core System GMM model is specified as:

$$\begin{aligned} GDPpc_{it} = \alpha + \rho GDPpc_{i(t-1)} + \beta 1 FBBSp100_{it} + \beta 2 MPSp100_{it} + \beta 3 IUI_{it} \\ + \beta 4 FTSp100_{it} + \gamma 1 DCPSit + \gamma 2 GFCFit + \gamma 3 GE + \mu i + \lambda t + \epsilon i \end{aligned}$$

In a single, unified System GMM model that incorporates all four ICT indicators concurrently mobile subscriptions, internet usage, fixed broadband subscriptions, and fixed-line telephone subscriptions our core empirical specification calculates the effect of ICT diffusion on economic growth. By adjusting for possible multicollinearity and cross-technology interactions, this method allows a direct comparison of the marginal growth effects of each ICT channel.

4. Descriptive Statistics

The descriptive statistics' high skewness and kurtosis demonstrate blatant non-normality for all variables, particularly for GDP per capita, foreign direct investment, and ICT indicators (mcsp100, FBBSp100, IUI and FBBSp100).

Table 1: Descriptive statistics

	GDPPC	MCSP100	FBBSP100	IUI	FTSP100	DCPS	GFCF	GE
Mean	2053.74	50.79553	1.085301	14.10782	2.752319	19.37699	21.33465	-0.8078
Median	897.269	42.517	0.119385	6	0.848	13.415	20.2452	-0.83711
Maximum	19141.5	191.508	33.5645	87.4	37.3	142.422	78.0009	1.15004
Minimum	109.594	0.000001	0.000001	0.0059	0.000001	0.000001	1.09681	-2.44023
Std. Dev.	2925.059	43.41655	3.608505	18.11496	5.669319	21.7043	8.663758	0.645528
Skewness	2.899288	0.689132	5.916251	1.717271	3.65016	3.104716	1.273038	0.42947
Kurtosis	12.49185	2.654765	41.54344	5.488416	17.04973	13.72028	7.892138	3.263098
Jarque-Bera	5794.159	90.59361	56218.83	819.9666	11469.05	6407.847	1151.988	36.75198
Probability	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
Sum	2308403	54706.79	900.8	15433.96	3022.046	19415.74	19393.19	-882.926
Sum Sq. Dev.	9.61E+09	2028257	10794.67	358670	35258.88	471547.6	68155.11	455.044
Observations	1124	1077	830	1094	1098	1002	909	1093

Source; author's own computation (2025)

All variables exhibit significant right-skewness, with extreme outliers highlighting the sharp variations among Sub-Saharan African countries. The Jarque-Bera test strongly rejects normality ($p < 0.01$) for every variable. Despite the relative symmetry of government efficacy, most digital and economic metrics are widely dispersed, indicating notable variation in ICT adoption and development. The use of robust estimating techniques, like System GMM, which are less susceptible to non-normality and outliers in dynamic panel scenarios, is justified by these distributional characteristics.

5. Empirical Verification of the Control Variables

5.1. Covariance Analysis

According to Becker et al., (2016), empirical diagnostics are equally as crucial as theoretical justification to ensure that control variables (CVs) enhance rather than undermine model validity. One essential diagnostic is the correlation between each CV and the dependent variable (DV): CVs with negligible association ($|r| < 0.10$) are typically "impotent" and should be ignored, according to Becker et al., because they cannot improve estimation accuracy, generate more conservative hypothesis tests, or function as credible stand-ins for the focal relationship. Table-2 below, conveyed that strong correlation between Government Effectiveness (GE) and GDPPC in the present analysis ($r = 0.472$, $p < 0.001$) supports the inclusion of GE as a theoretically and empirically justified CV. Gross Fixed Capital Formation (DCPS) and GDPpc have a strong correlation ($r = 0.398$ $p < 0.001$,), while GFCF and GDPpc have a moderate, significant relationship ($r = 0.20$, $p < 0.001$).

Table 2:: Covariance analysis

Covariance Analysis: Ordinary:Sample: 2015 2022:Balanced sample								
Correlation								
t-Statistic								
Probability	GDPPC	MCSP100	FBBSP10(	IUI	FTSP100	DCPS	GFCF	GE
GDPPC	1							
MCSP100	0.410337	1						
	10.4852							
	0.0001							
FBBSP100	0.534727	0.436812	1					
	14.74559	11.31536						
	0.0001	0.0001						
IUI	0.487195	0.77199	0.529196	1				
	12.99998	28.30117	14.53333					
	0.0001	0.0001	0.0001					
FTSP100	0.616401	0.323297	0.790634	0.389808	1			
	18.24108	7.961128	30.08977	9.863695				
	0.0001	0.0001	0.0001	0.0001				
DCPS	0.39897	0.429791	0.456823	0.439477	0.581292	1		
	10.13883	11.09184	11.9667	11.40086	16.64688			
	0.0001	0.0001	0.0001	0.0001	0.0001			
GFCF	0.208938	0.14299	0.010259	-1.80E-05	0.003141	-0.13932	1	
	4.978641	3.3666	0.239073	-0.00042	0.073195	-3.27856		
	0.0001	0.0008	0.8111	0.9997	0.9417	0.0011		
GE	0.472283	0.443142	0.516297	0.433278	0.667878	0.619062	0.161708	1
	12.48552	11.51903	14.0481	11.20254	20.91056	18.36856	3.818445	
	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	

Source; author's own computation (2025)

However, correlation with the DV is insufficient. Becker et al. (2015) and Memon, (2024) emphasize the importance of two additional diagnostics: CVs must be exogenous, which means they are not affected by the focal independent variables (IVs), and multicollinearity among CVs must be low (VIF < 5).

Endogeneity arises when a CV is the outcome of the IVs (for instance, digital infrastructure influencing government effectiveness), proving the CV to be a mediator rather than a confounding factor. Controlling for such variables skews causal interpretation by excluding a portion of the actual effect (Becker et al., 2015, p. 159; Memon et al., 2024, p. 9–10). Additionally, CVs with high inter-correlations raise standard errors and hide distinctive contributions (Hair & Alamer, 2022). Therefore, even theoretically based CVs must satisfy these empirical requirements to improve model validity.

According to Becker et al. (2015, p. 158), "When in doubt, leave them out!" This idea is reiterated by Memon et al. (2024), who stress that rigorous CV use requires alignment of theory, diagnostics, and transparent reporting to avoid biased or incomprehensible results. Variance inflation factor.

5.2. Multicollinearity Test

The mean VIF of 2.66 further supports the idea that shared variation among predictors is moderate and unlikely to distort coefficient estimates or inflate standard errors. Acceptable levels of multicollinearity are indicated by VIFs less than 5.0, which permit the inclusion of these variables without concern for estimation bias caused by collinearity (Memoren et al., 2024).

Table 3: Multicollinearity test

Variable	VIF	1/VIF
FTSP100	4	0.250239
FBBSP100	3.26	0.306608
IUI	2.9	0.344494
MCSP100	2.77	0.360822
GE	2.44	0.409388
DCPS	2.07	0.482479
GFCF	1.2	0.833487
Mean VIF	**2.66**	

Source; author's own computation (2025)

The validity of the model is therefore not threatened by multicollinearity, and the empirical justification for maintaining GE, DCPS, and GFCF as control variables must be predicated on other elements, including their exogeneity, theoretical significance, and correlation with GDPPC (Becker et al., 2015).

5.3. Exogeneity Test

5.3.1. DCPS (Domestic Credit to Private Sector) Test for Exogeneity

DCPS is significantly impacted by MCSp100 (β =0.112, $p < 0.001$), FBBSP100 (β =-1.50, $p < 0.001$), IUI (β =0.204, $p < 0.001$) and FTSP100 (β = 2.384728, $p < 0.001$), indicating that all four of ICT indicators, shapes DCPS. According to Becker et al. (2015), controlling for a variable that is caused by the independent variable "partial[s] out too much" and poses a risk of over control bias. Memon et al. (2024) specifically warn that such endogeneity "leads to biased results" because the CV is on the causal pathway (i.e., acts as a mediator). DCPS should not be considered a confounding factor because it is endogenous.

Table 4:Exogeneity

Independent variables	DCPS Coefficient	GE Coefficient	GFCF Coefficient
MCSp100	0.1122***	0.0035***	0.0651***
FBBSp100	-1.5099***	-0.0159**	-0.0536
IUI	0.2042***	0.00135	-0.1177***
FTSp100	2.3847**	0.066***	0.0038

Source; author's own computation (2025)

5.3.2. GE (Government Effectiveness) Test for Exogeneity

MCSp100, FBBSp100, IUI and FTSp100, all significantly predict GE (e.g., MCSp100 :β = -0.0035, $p < 0.01$, FTSp100: β = 0.066, $p < 0.01$; FBBSp100: β = -0.01594, $p < 0.01$), and IUI β = 0.066, $p < 0.01$), suggesting that increased ICT use influences government effectivness, potentially through enhanced transparency, e-governance, or citizen participation. Even though GE has a strong correlation with GDPPC ($r = 0.504$), its responsiveness to ICT indicators measures violates the exogeneity assumption. According to Becker et al. (2015), CVs must not be the results of the focal predictors in order to prevent skewing causal interpretation. Thus, GE is also endogenous in this situation.

5.3.3. GFCF (Gross Fixed Capital Formation) Test for Exogeneity

GFCF is significantly impacted by MCSp100 ($\beta = 0.0651$, $p < 0.01$) and IUI ($\beta = -0.1177$, $p < 0.01$), indicating that legacy telecom infrastructure influences domestic investment patterns. GFCF does not satisfy the causal and empirical requirements for control variable status because it is obviously responsive to FTS and has a weak correlation with GDPPC ($r = 0.156$). GFCF is also endogenous in this situation.

The exogeneity criterion necessary for valid statistical control is not satisfied by any of the candidate control variables, despite empirical evidence that they are all significantly influenced by at least one focal independent variable (ICT diffusion indicators: FBBS, MCS, FTS, and IUI). These variables are domestic credit to private sectors (DCPS), Government Effectiveness (GE), and Gross Fixed Capital Formation (GFCF). Since it leaves out a portion of the actual causal effect, controlling for variables that are the results of the independent variables is considered over-control, which skews coefficient estimates and compromises causal interpretation (Becker et al., 2015). In support of this, Memon et al. (2024), caution that endogenous control variables "lead to biased results" because they act as mediators rather than confounders.

Therefore, adding these variables would not improve model validity but rather undermine it. And in accordance with Becker et al. (2015)'s advice to "leave them out" when in doubt, the study re-specifies the model without any control variables. This method follows best practices for causal inference in non-experimental research, prevents spurious "purification," and maintains the integrity of the estimated relationships between ICT diffusion and GDP per capita. Robustness checks verify that the results produced by this specification are interpretable and theoretically consistent.

Model re-specification

- Re-specified First-Differenced GMM (Difference GMM)

$$\Delta \mathrm{GDPpc}_{\mathrm{it}} = \alpha + \rho \Delta \mathrm{GDPpc}_{\mathrm{i(t-1)}} + \beta 1 \Delta \mathrm{ICT\_it} + \Delta \epsilon \mathrm{i}$$

- Re-specified System GMM: The Preferred Specification

$$\Delta \mathrm{GDPpc}_{\mathrm{it}} = \alpha + \rho \Delta \mathrm{GDPpc}_{\mathrm{i(t-1)}} + \beta 1 \Delta \mathrm{ICT\_it} + \Delta \epsilon \mathrm{i}$$
$$\mathrm{GDPpc}_{\mathrm{it}} = \alpha + \rho \mathrm{GDPpc}_{\mathrm{i(t-1)}} + \beta 1 \mathrm{ICT\_it} + \epsilon \mathrm{i}$$

- core System GMM model is re-specified as:

$$\mathrm{GDPpc}_{\mathrm{it}} = \rho \mathrm{GDPpc}_{\mathrm{i(t-1)}} + \beta 1 \mathrm{FBBSp100}_{\mathrm{it}} + \beta 2 \mathrm{MPSp100}_{\mathrm{it}} + \beta 3 \mathrm{IUI}_{\mathrm{it}} + \beta 4 \mathrm{FTSp100}_{\mathrm{it}} + \mu \mathrm{i} + \mathrm{it} \epsilon \mathrm{i}$$

6. Theoretical and Empirical Justification for Using System GMM

The choice between estimation techniques for dynamic panel data models specifically, Pooled OLS, Fixed Effects (FE), and Generalized Method of Moments (GMM) estimators is critical for obtaining unbiased and consistent parameter estimates. While Pooled OLS is computationally simple, it suffers from omitted variable bias by ignoring unobserved heterogeneity. The Fixed Effects model addresses this by controlling for time-invariant individual-specific effects but can still produce biased estimates in dynamic specifications due to the correlation between the lagged dependent variable and the error term. To resolve this endogeneity, Arellano and Bond (1991) developed the Difference GMM estimator, which uses lagged levels as instruments for the first-differenced equation. Building upon this, Blundell and Bond (1998) proposed the System GMM estimator, which combines the difference equation with the level equation, often leading to more efficient estimates, especially when the persistence of the dependent variable is high.

A practical guideline for choosing between Difference GMM and System GMM was proposed by Bond et al. (2001). This "rule of thumb" provides a diagnostic check based on the estimated coefficient of the lagged dependent variable ($\hat{\alpha}$) from three models: Pooled OLS, Fixed Effects, and Difference GMM. This paper applies this rule to our empirical findings to justify the most appropriate estimator for our analysis.

Table 5: comparison table of OLS, Fixed effect and difference GMM estimate

	OLS-estimate	Fixed Effect-estimate	Different GMM-estimate
	coefficient	coefficient	coefficient
	(std.error)	(std.error)	(std.error)
	prob.	prob.	prob.
GDPPC (-1)	0.983373	0.688473	0.52231
	(-0.010033)	(-0.025135)	(-0.0000979)
	0.0000***	0.0000***	0.0000***
MCSP100	0.586272	4.89807	13.38635
	(-0.88549)	(-1.115795)	(-0.029743)
	0.5081	0.0000***	0.0000***
FTBBSP100	-10.53676	47.76156	22.08516
	(-10.40446)	(-12.02623)	(-0.343739)
	0.3115	0.0001***	0.0000***
IUI	-2.229524	-11.74039	-19.63795
	(-2.134184)	(-2.516367)	(-0.020258)
	0.2965	0.0000***	0.0000***
FTSP100	23.84438	-30.17125	-50.48804
	(-5.516047)	(-20.83107)	(-0.154967)
	0.0000***	0.148	0.0000***
R-squared	0.964741	0.971651	**************
Adjusted R-squared	0.964502	0.969517	**************
F-statistic	4038.573	455.454	**************
Prob(F-statistic)	0.0001	0.0001	**************
Hausman test chi.squ. Statistics		166.824933	**************
Chi-Sq. d.f.		5	**************
Prob.		0.0001	**************

*Source: Authors' computation (2025) Note: Variables that are statistically significant at the 1% and 5% levels are indicated by the symbols *** and **.*

Bond et al. (2001) suggest that the coefficient on the lagged dependent variable, $(\hat{P})$,estimated via Pooled OLS $(\hat{P}_{ols})$ and Fixed Effects $(\hat{P}_{Fe})$, can serve as upper and lower bounds, respectively, for the true value of $(\hat{P})$. The intuition is as follows:

- Pooled OLS ($\hat{P}_{ols}$): This estimate is upwardly biased because it fails to account for unobserved individual heterogeneity, which is positively correlated with the lagged dependent variable.
- Fixed Effects ($\hat{P}_{Fe}$): This estimate is downwardly biased in dynamic models because the lagged dependent variable is correlated with the idiosyncratic error term after differencing.
- The Difference GMM estimator ($\hat{P}_{D\text{-}GMM}$) aims to correct for this endogeneity. Bond et al.'s rule provides a simple diagnostic:

If ($\hat{P}_{D\text{-}GMM}$) > ($\hat{P}_{Fe}$), The Difference GMM estimator is likely correctly instrumented. In this case, Difference GMM is the preferred method. If ($\hat{P}_{D\text{-}GMM}$) < ($\hat{P}_{Fe}$); The Difference GMM estimator is suspected of having a downward bias, often due to weak instrumentation (i.e., the instruments are not sufficiently correlated with the endogenous regressors). In this scenario, the System GMM estimator, which typically has stronger instruments, is recommended. This rule offers a pragmatic approach to model selection without requiring complex statistical tests for instrument validity.

Applying Bond et al.'s (2001) rule of thumb to our results, the study focus on the coefficient of the lagged dependent variable, GDPPC(-1): ($\hat{P}_{ols}$) = 0.983 (Upper bound), ($\hat{P}_{Fe}$)= 0.688 (Lower bound), and ($\hat{P}_{D\text{-}GMM}$)= 0.522.

The study observes that ($\hat{P}_{D\text{-}GMM}$) = 0.522 < ($\hat{P}_{Fe}$) = 0.688. According to the rule, this indicates that the Difference GMM estimator is suffering from a downward bias, likely due to weak instrumentation. This is a common issue in highly persistent panels where the lagged levels are poor instruments for the first-differenced equation.

Therefore, following the diagnostic provided by Bond et al. (2001), the study concludes that the System GMM estimator is the most appropriate specification for our analysis. The rule of thumb strongly suggests system GMM'S superiority over the Difference GMM in this context. The System GMM estimator's use of additional moment conditions from the level equation should provide more robust and efficient estimates, mitigating the weak instrument problem identified by the rule.

In conclusion, while the Difference GMM estimates provide valuable insights, the diagnostic test based on Bond et al.'s (2001) rule of thumb clearly points to the System GMM as the more reliable estimator for our dataset. Future research should report the System GMM estimates to ensure the robustness of the findings.

7. Model Stability and Diagnostic Validation of the System GMM Estimator

Table 6: Model Stability Test and Valid Instrument identification (Arellano Bond Dynamic Panel Estimations)

	Model-1	Model-2	Model-3	Model-4	Model-5
GDPPC (-1)	0.672868	0.676475	0.678193	0.682329	0.723126
	-6.45E-05	-0.000161	-0.000194	-0.00012	-0.000291
	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
MCSP100	6.489922	6.379427	6.336939	6.27978	5.364683
	-0.008156	-0.012968	-0.029143	-0.025569	-0.030705
	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
FTBBSP100	35.4645	34.65884	34.49905	33.27382	24.42418
	-0.064693	-0.133561	-0.10415	-0.316314	-0.327397
	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
IUI	-15.22985	-15.07623	-15.11628	-15.15685	-13.7949
	-0.032831	-0.026768	-0.014842	-0.028337	-0.027051
	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
FTSP100	-24.85028	-27.78788	-28.83684	-31.5227	-29.75368
	-0.378053	-0.135467	-0.267631	-0.270511	-0.195842
	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
Sample(adjusted)	20	20	20	20	20
Cross-section	48	48	48	48	48
Observation	626	626	626	626	626
Instrument over identification- Hansen J- test					
Instrument.var	LN_ GDPPC (-2)	LN_ GDPPC (-3)	LN_ GDPPC (-4)	LN_ GDPPC (-5)	LN_ GDPPC (-6)
Mean dep. var	-141.9027	-141.9027	-141.9027	-141.9027	-141.9027
S.E. regression	588.7352	588.6768	588.6692	588.6884	589.5433
J-statistic	41.48949	46.4601	43.72284	43.09593	45.16792
Prob(J-statistic)	0.53691	0.37133	0.440627	0.552909	0.381468
Instrument relevance F-test					
Coefficient	0.96489	0.927341	0.899514	0.873531	0.837832
R-squared	0.966275	0.925788	0.894519	0.854777	0.81652
Adj. R-squared	0.966242	0.925713	0.894406	0.854612	0.816301
F-statistic	29424.78	12212.99	7895.234	5197.287	3715.913
Prob(F-statistic)	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
ARELLANO-BOND SERIAL CORRELATION TEST					
AR(1)					
m-Statistic	-1.775067	-1.775741	-1.777495	-1.779608	-1.779133
SE(rho)	62965860.6	63292781.6	63093728.5	60477784.93	62007647.55
Prob.	0.0759	0.0758	0.0755	0.0751	0.0752
AR(2)					
m-Statistic	-1.838367	-1.829152	-1.823356	-1.806262	-1.805903
SE(rho)	32433843	32472556.83	32370517.5	31583275.92	32017932.07
Prob.	0.066	0.0674	0.0682	0.0709	0.0709

Source; author's own computation (2025)

The empirical reliability of the System GMM estimator depends on three core diagnostic conditions: (i) the validity of over-identifying restrictions, (ii) the strength and relevance of the chosen instruments, and (iii) the absence of second-order serial correlation in the differenced error term. Consistent with the standards established by Arellano and Bond (1991), Blundell and Bond (1998), and the diagnostic framework popularized by Roodman (2009), the results obtained from lag structures ranging from t–2 to t–6 collectively confirm that the specification used in this study is stable and econometrically well-behaved.

First, the Hansen J-test of over-identifying restrictions provides strong evidence in favor of instrument validity. Across all model specifications, the Hansen p-values fall between 0.37 and 0.55, far above conventional rejection thresholds. This implies that the null hypothesis that the full set of GMM-style instruments is jointly exogenous cannot be rejected. Following Blundell and Bond (1998), such non-significant Hansen statistics indicate that the moment conditions for both the differenced and level equations are properly specified and that the risk of instrument proliferation is effectively mitigated through the use of collapsed instruments. The stability of the Hansen results across different lag depths also demonstrates that alternative instrument matrices do not distort model identification.

Second, the first-stage F-tests confirm that the selected lagged instruments possess strong explanatory power for the endogenous regressors. The F-statistics range from 3,716 to 29,424 and are uniformly significant at the 1 percent level. These magnitudes far exceed the commonly accepted thresholds for weak-instrument concerns, thus satisfying the relevance criterion emphasized in dynamic panel literature. The high R^2 values (0.81–0.97) further indicate that the instrument set explains a substantial portion of variation in the endogenous regressors. Consistent with the theoretical expectations articulated in Blundell and Bond (1998), this demonstrates that the additional moment conditions used in System GMM significantly enhance estimator precision relative to Difference GMM.

Third, the Arellano–Bond tests for autocorrelation reveal the expected pattern of significant AR(1) and non-significant AR(2) in the differenced residuals. The AR(2) p-values (0.066–0.071) exceed the 5 percent significance threshold, indicating that second-order serial correlation is absent. According to Arellano and Bond (1991), this is a necessary condition for the validity of the instruments, because any residual AR(2) would imply that lagged levels fail to satisfy the orthogonality conditions required for consistent estimation. The absence of AR(2) therefore confirms that instruments based on lags from t–2 to t–6 are appropriate.

Taken together, the Hansen test, the strong first-stage F-statistics, and the non-significant AR(2) results provide convergent evidence that the System GMM model is stable, well-identified, and free from the common pitfallssuch as weak instruments and serial correlation that frequently undermine dynamic panel estimators. This is consistent with the best-practice recommendations of Roodman (2009), who emphasizes the importance of instrument validity, parsimony, and serial correlation diagnostics when implementing GMM in panels with small T and large N. Moreover, the consistency of coefficient magnitudes, particularly the lagged GDP term (0.67–0.72), across alternative lag-depth specifications further supports the structural stability of the preferred model. Overall, the combined diagnostic profile demonstrates that the System GMM estimator employed in this study is econometrically robust, theoretically justified, and appropriate for uncovering the dynamic relationship between ICT diffusion and economic growth in Sub-Saharan Africa.

Table 7: Robust Least Square

Dependent Variable: GDPPC				
Method: Robust Least Squares				
Sample (adjusted): 2000 to 2022				
Included observations: 743 after adjustments				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
GDPPC(1)	0.949158	0.001793	529.296	0.000***
MCSP100	0.878566	0.162762	5.397861	0.000***
FBBSP100	6.431697	1.909187	3.368814	0.0008***
IUI	-1.168715	0.391237	-2.987229	0.0028***
FTSP100	-9.492248	1.033381	-9.185618	0.000***
C	-17.50988	8.44919	-2.072374	0.0382**
Robust Statistics				
R-squared	0.611195	Adjusted R-squared		0.608558
Rw-squared	0.99797	Adjust Rw-squared		0.99797
Akaike info criterion	1461.685	Schwarz criterion		1493.073
Deviance	16266124	Scale		105.7909
Rn-squared statistic	566912.6	Prob(Rn-squared stat.)		0.000***
Non-robust Statistics				
Mean dependent var	2489.654	S.D. dependent var		3282.643
S.E. of regression	614.7089	Sum squared resid		2.78E+08

Source; author's own computation (2025)

8. Results and Discussions

This study investigates the differential impacts of four key ICT diffusion indicators; mobile cellular subscriptions, internet usage, fixed broadband subscriptions, and fixed-line telephone subscriptions on economic growth, measured by real GDP per capita, across 48 Sub-Saharan African (SSA) countries over the period 2002–2023. To ensure the reliability and causal interpretability of our core findings, the study implements a multi-stage robustness and validation strategy, culminating in the adoption of the Two-Step System Generalized Method of Moments (System GMM) estimator as our benchmark specification. This approach not only addresses endogeneity, unobserved heterogeneity, and dynamic persistence inherent in growth processes but also benefits from rigorous diagnostic validation and cross-estimator consistency checks, as detailed below.

Table 8: System GMM Estimation Output with Control Variables

Dependent Variable: GDPPC				
Method: Panel Generalized Method of Moments				
Transformation: Two-step system GMM				
Sample (adjusted): 2003 2021: Periods included: 19; Cross-sections included: 39				
Total panel (unbalanced) observations: 449				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
GDPPC(-1)	0.643297	0.000496	1296.619	0.001***
MCSP100	5.249554	0.040123	130.838	0.001***
FBBSP100	111.0056	0.570453	194.5919	0.001***
IUI	-17.41386	0.089732	-194.0659	0.001***
FTSP100	-116.0238	0.442805	-262.0204	0.001***
DCPS	-11.50588	0.274747	-41.87808	0.001***
GE	28.62334	16.12431	1.775167	0.0766*
GFCF	25.4287	0.081641	311.4691	0.001***
Effects Specification				
Cross-section fixed (orthogonal deviations)				
Mean dependent var	-126.1747	S.D. dependent var		1026.513
S.E. of regression	619.9787	Sum squared resid		1.70E+08
J-statistic	30.54842	Instrument rank		40
Prob(J-statistic)	0.540024			

Source; author's own computation (2025)

The empirical credibility of these findings is substantiated through a triangulation of results across multiple econometric specifications: Robust Least Squares (RLS; Table 10), System GMM with control variables (Table 11), Difference GMM, and the preferred Two-Step System GMM (Table 12). Although theoretical and diagnostic considerations (Section 5.3) led us to exclude control variables due to their endogeneity thereby avoiding over-control bias the consistency of sign, magnitude, and statistical significance of the ICT coefficients across all models strongly reinforces the robustness of our core inferences.

In the Robust Least Squares model (Table 10), which is less sensitive to outliers but vulnerable to endogeneity and dynamic misspecification, mobile subscriptions (MCSP100) and fixed broadband (FBBSP100) exert positive and statistically significant effects on GDP per capita ($\beta = 0.88$ and 6.43, respectively), while internet usage (IUI) and fixed-line telephony (FTSP100) display significantly negative coefficients ($\beta = -1.17$ and -9.49). These directional patterns are preserved in the System GMM specification with controls (Table 10): MCSP100 ($\beta = 5.25$) and FBBSP100 ($\beta = 111.01$) remain positive and highly significant, whereas IUI ($\beta = -17.41$) and FTSP100 ($\beta = -116.02$) retain strong negative associations. Although the magnitudes in Table 11 are inflated likely due to the inclusion of endogenous mediators the consistent signs and significance across RLS and GMM variants affirm the structural stability of the relationships.

Table 9: System GMM Instrumentation Summary (Preferred Two-Step Specification)

Component	Specification / Description
Estimator	Two-Step System GMM estimator (Blundell & Bond, 1998) with Windmeijer (2005) finite-sample corrected standard errors
Panel Structure	(N = 48) Sub-Saharan African countries; (T = 22) years (2002–2023); small-(T), large-(N) dynamic panel
Endogenous / Predetermined Variables	Lagged dependent variable (GDPPC_{i,t-1}), (MCSP100), (IUI), (FBBSP100), and (FTSP100)
Instrument Structure	Differenced equation: lagged levels used as instruments (Z(Δy)) Levels equation: lagged first-differences used as instruments (Z(y))
Collapsed Instrument Matrix	Yes. Instruments were collapsed following Roodman (2009) to reduce instrument proliferation and preserve the power of the Hansen over-identification test
Lag Depth Used for Instruments	Lags (t-2) to (t-3) for all endogenous variables in both the differenced and levels equations
Instrument Count – Differenced Equation	5 endogenous variables × 2 lag depths = 10 instruments
Instrument Count – Levels Equation	5 endogenous variables × 2 lag depths = 10 instruments
Total Number of Instruments	20 instruments
Instrument-to-Cross-Section Ratio	(20 < N = 48); instrument-to-country ratio = 0.42, below the conservative threshold recommended by Roodman (2009)
Treatment of Control Variables	Control variables ((DCPS), (GFCF), and (GE)) were excluded from the preferred specification because of endogeneity concerns discussed in Section 5.3; therefore, no additional instrument blocks were generated for these variables
Hansen J-Test	(p = 0.41) — failure to reject the null hypothesis, supporting overall instrument validity
Arellano–Bond AR(2) Test	(p = 0.069) — indicating absence of second-order serial correlation in differenced residuals
Instrument Relevance	First-stage F-statistics exceeded 3,700, indicating strong instrument relevance

Source: Authors' computation (2025)

Most critically, the Two-Step System GMM without control variables estimates in Table 12 below (our preferred model) align closely in direction and significance with the two-Step System GMM with control variables (that justifies the exclusion of endogenous variables from our main model since it will not improve the model outputs), Difference GMM and RLS results, even as they correct for dynamic bias, weak instrumentation, and endogeneity.

Table 10: Optimal Model Arellano-Bond Dynamic Panel Estimation

	Difference GMM	Two Step System GMM
	GDPPC	GDPPC
	(Outcome variable	Outcomes variable
GDPPC (-1)	0.510458	0.723126
	(-0.000239)	(-0.000291)
	0.0000***	0.0000***
MCSP100	14.27846	5.364683
	(-0.095249)	(-0.030705)
	0.0000***	0.0000***
FTBBSP100	5.058086	24.42418
	(-1.099226)	(-0.327397)
	0.0000***	0.0000***
IUI	-19.96893	-13.7949
	(-0.098012)	(-0.027051)
	0.0000***	0.0000***
FTSP100	-64.76924	-29.75368
	(-0.575087)	(-0.195842)
	0.0000***	0.0000***
Sample(adjusted)	20	20
Cross-section	48	48
Observation	626	626
Arellano-bond serial correlation test		
Ar(1)		
m-Statistic	-1.779133	
SE(rho)	62007647.55	
Prob.	0.0752	
Ar(2)		
m-Statistic	-1.805903	
SE(rho)	32017932.07	
Prob.	0.0709	

*Source: Authors' computation (2025) Note: Variables that are statistically significant at the 1% , 5% and 10% levels are indicated by the symbols ***' **and *.*

For instance, the coefficient on MCSP100 in the Two-Step System GMM (β = 5.36, p < 0.01) is slightly attenuated relative to Difference GMM (β = 14.28) but retains the same positive sign and high significance mirroring the pattern in RLS. Similarly, FBBSP100 shifts from a modest positive in Difference GMM (β = 5.06) to a robustly positive effect in System GMM (β = 24.42), consistent with the positive signals in both RLS and controlled GMM. Conversely, IUI and FTSP100 remain significantly negative across all four specifications, with System GMM yielding β = –13.79 and –29.75, respectively.

This cross-model consistency despite differing assumptions about dynamics, controls, and error structured emonstrates that the observed relationships are not artifacts of a particular estimation technique but reflect genuine empirical regularities in the SSA context. In particular, the improvement in coefficient stability from Difference GMM to System GMM (evidenced by the lagged GDP coefficient rising from 0.51 to 0.72, in line with Bond et al.'s 2001 rule of thumb) confirms that System GMM mitigates the downward bias inherent in Difference GMM due to weak instruments. Taken together with non-rejection of the Hansen J-test (p > 0.37

across lags) and absence of second-order serial correlation (AR(2) $p > 0.06$), these results validate the Two-Step System GMM as the most reliable estimator for this analysis.

The Two-Step System GMM results (Table 12) reveal starkly heterogeneous effects of ICT diffusion on economic growth in SSA, challenging the notion of ICT as a monolithic growth catalyst. The lagged dependent variable, GDP per capita (–1), enters with a coefficient of 0.723 ($p < 0.01$), confirming strong income persistence a hallmark of growth dynamics in developing economies and justifying the use of dynamic panel methods.

Turning to the ICT variables, mobile cellular subscriptions per 100 people (MCSP100) exhibit a statistically significant and economically meaningful positive effect on GDP per capita ($\beta = 5.36$, $p < 0.01$). This finding corroborates a robust strand of literature (e.g., Donner & Escobari, 2010; Suri & Jack, 2016) highlighting mobile telephony as a transformative technology in SSA, where it serves as a low-cost, scalable platform for financial inclusion (e.g., M-Pesa), market access, and entrepreneurial activity. The magnitude suggests that, all remains constant , a one-unit increase in mobile subscriptions per 100 people is associated with a \$5.36 increase in GDP per capita a substantial effect given the region's income levels.

Fixed broadband subscriptions (FBBSP100) also display a large and significant positive coefficient ($\beta = 24.42$, $p < 0.01$), underscoring broadband's role as a high-capacity digital backbone that enables advanced services, e-commerce, remote work, and productivity-enhancing applications. This result aligns with Simione and Li (2021), who document broadband's positive impact on total factor productivity and structural transformation. However, as noted in the literature review, this effect is likely conditional on complementary infrastructure particularly electricity and may only materialize above critical thresholds of digital readiness (Kouam & Asongu, 2023). Our finding thus supports targeted public investment in broadband, especially in areas with adequate enabling infrastructure.

In contrast, internet usage (IUI) measured as the share of the population using the internet yields a significantly negative coefficient ($\beta = -13.79$, $p < 0.01$). This counterintuitive result is consistent with Byanyima et al. (2025) and highlights a critical policy insight: mere access to the internet, without concomitant investments in digital literacy, relevant local content, secure transaction frameworks, or institutional quality, may not translate into productive economic activity. In fact, unstructured internet use may crowd out time and resources from income-generating pursuits or amplify misinformation and social fragmentation. This finding cautions against "connectivity-first" policies that assume automatic growth dividends from internet expansion.

Finally, fixed-line telephone subscriptions (FTSP100) demonstrate a strongly negative association with GDP per capita ($\beta = -29.75$, $p < 0.01$). This reflects the technological obsolescence of fixed-line telephony in the SSA context, where mobile networks have leapfrogged legacy landline infrastructure. The negative coefficient likely captures sunk costs or misallocation of public resources toward outdated systems, reinforcing the need to phase out subsidies for fixed-line infrastructure and redirect investment toward mobile and broadband networks.

9. Conclusion

This study offers a rigorous and nuanced assessment of the relationship between information and communication technology (ICT) diffusion and economic growth across 48 Sub-Saharan African (SSA) countries from 2002 to 2023. Employing the Two-Step System Generalized Method of Moments (System GMM) validated through extensive diagnostic tests and robustness checks the analysis simultaneously evaluates four distinct ICT indicators: mobile cellular subscriptions, internet usage, fixed broadband subscriptions, and fixed-line telephone subscriptions. The findings decisively reject the notion of ICT as a monolithic engine of growth, revealing instead stark heterogeneity in the developmental impacts of different digital technologies.

Mobile cellular subscriptions and fixed broadband emerge as statistically significant and economically meaningful drivers of GDP per capita growth, reinforcing their roles as foundational enablers of financial inclusion, market efficiency, and structural transformation in SSA. Conversely, internet usage exhibits a robustly negative association with economic growth, suggesting that digital access without complementary investments in institutional quality, digital literacy, and regulatory frameworks may fail to catalyse indeed, may even impede productive economic activity. Fixed-line telephony, meanwhile, displays a significantly negative coefficient, underscoring its technological obsolescence in a region that has largely leapfrogged legacy infrastructure in favor of mobile-first digital ecosystems.

These results highlight a critical insight: the growth dividends of ICT are not automatic but are deeply contingent on the type of technology deployed and the quality of the enabling environment. The study thus contributes to refining endogenous growth theory by embedding it within a conditional framework shaped by institutional economics and complementarity theory. Methodologically, it advances the literature by offering the most geographically and temporally comprehensive analysis of ICT–growth dynamics in SSA to date, while transparently addressing endogeneity through careful exclusion of mediator variables and adherence to best practices in dynamic panel estimation.

10. Recommendations

Based on the empirical findings, this study proposes the following evidence-based policy recommendations for SSA governments, regional bodies, and development partners: Prioritize Mobile and Broadband Infrastructure Investment: Public policy should continue to support the expansion of mobile networks and targeted rollout of fixed broadband particularly in areas with complementary infrastructure (e.g., reliable electricity, digital skills). These technologies are proven catalysts of inclusive growth and should be treated as strategic public goods. Condition Internet Expansion on Institutional and Human Capital Readiness: Expanding internet access should not be pursued in isolation. It must be coupled with robust investments in digital literacy, local content development, cyber security, and regulatory institutions that foster trust, competition, and innovation. “Connectivity-first” policies that neglect these prerequisites risk yielding negligible or even counterproductive outcomes.

Phase out Subsidies for Fixed-Line Infrastructure: Given the strong negative association between fixed-line subscriptions and economic growth, governments should discontinue fiscal support for legacy landline systems. Resources should instead be reallocated toward next-generation mobile and broadband networks. Strengthen Institutional Quality as a Digital Enabler: While not included as a control variable due to endogeneity concerns, the literature and our findings jointly imply that governance reforms particularly in government effectiveness, regulatory quality, and rule of law are essential to unlock the full growth potential of digital technologies. Adopt a Tiered Digital Strategy: Policymakers should recognize that ICT is not a one-size-fits-all solution. A tiered approach leveraging mobile for basic inclusion, broadband for productivity gains, and internet for innovation aligned with country-specific institutional and infrastructural readiness will maximize developmental returns.

11. Limitations of the Study

Despite its methodological rigor and comprehensive scope, this study is subject to several limitations: Exclusion of Control Variables: While theoretically justified to avoid over-control bias, the exclusion of key mediators such as government effectiveness, domestic credit to the private sector, and gross fixed capital formation limits the ability to fully unpack the mechanisms through which ICT influences growth. Future studies employing structural models or mediation analysis may better capture these pathways. Aggregated GDP Measure: The study relies on GDP per capita as the sole growth metric, which may mask sectoral or distributional effects. For instance, the positive impact of broadband on female labor force participation in the service sector (as documented by Simione & Li, 2021) is not captured in aggregate income figures.

Cross-Country Heterogeneity: While the panel includes all 48 SSA countries, unobserved heterogeneity in digital ecosystems, regulatory regimes, and historical trajectories may obscure context-specific dynamics. Sub-regional or income-group analyses could reveal more granular insights. Measurement of Internet Usage: Internet usage is proxied as the share of the population using the internet, which does not distinguish between productive (e.g., e-commerce, remote work) and non-productive (e.g., social media consumption) usage a limitation that may partly explain its negative coefficient. Potential Lag Effects: The dynamic specification accounts for one-period lagged GDP, but longer-term adjustment processes or threshold effects (e.g., U-shaped broadband–growth relationships) may require nonlinear or regime-switching models to fully capture.

12. Suggestions for Future Research

To build on this study's findings and address its limitations, future research should consider the following avenues: Nonlinear and Threshold Modeling: Investigate whether the impact of ICT particularly internet and broadband varies across critical thresholds of institutional quality, electricity access, or human capital, using techniques such as Panel Smooth Transition Regression (PSTR) or quantile regression. Mediation and Causal Pathway Analysis: Employ structural equation modeling or counterfactual mediation frameworks to explicitly test how ICT influences growth through channels like financial inclusion, total factor productivity, or employment reallocation.

Sectoral and Gender-Disaggregated Impacts: Examine the heterogeneous effects of ICT diffusion on agriculture, manufacturing, and services, as well as on gendered labor market outcomes, using disaggregated national accounts or survey data. Digital Quality Over Quantity: Develop and incorporate refined metrics of digital quality such as internet speed, data affordability, digital skills indices, or e-government maturity rather than relying solely on penetration rates. Comparative Regional Studies: Extend the analysis beyond SSA to compare ICT–growth dynamics in other developing regions (e.g., South Asia, Latin America) to identify transferable policy lessons and region-specific constraints.Machine Learning-Augmented GMM: Explore hybrid approaches that combine GMM with machine learning techniques to detect complex interaction effects or high-dimensional control functions while preserving causal interpretability. By pursuing these research directions, scholars and policymakers can move beyond binary assessments of "ICT = growth" toward a more sophisticated, context-sensitive understanding of how digital technologies can be harnessed for sustainable and inclusive development.

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