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DIGITALIZATION FOR ENVIRONMENTAL SUSTAINABILITY: EVIDENCE FROM THE ICT–CARBON EMISSIONS NEXUS IN SUB-SAHARAN AFRICA

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ABSTRACT

The rapid expansion of digitalization across Sub-Saharan Africa has created new opportunities for economic development, yet its impact on environmental sustainability remains unclear. This study investigates the relationship between digitalization and environmental quality in 41 countries in Sub-Saharan Africa over the period 2004–2023. Digitalisation is measured through internet usage, mobile subscriptions, and a composite ICT index, while carbon dioxide (CO_2) emissions serve as the indicator of environmental quality. Prior to estimation, a collection of diagnostic tests was conducted to ensure methodological rigour and guide model selection. Employing a dynamic two-way fixed effects framework that accounts for both country-specific and time-specific effects, the findings indicate that digitalization contributes to improved environmental quality through reductions in CO_2 emissions. Renewable energy consumption is also found to mitigate environmental degradation, whereas economic growth, trade openness, and foreign direct investment tend to increase emissions. Notably, the Dumitrescu–Hurlin panel Granger causality test confirms a bidirectional causal relationship between ICT and CO_2 emissions, suggesting a feedback mechanism between digitalisation and environmental outcomes. Overall, the findings suggest that digitalization can support environmental sustainability in Sub-Saharan Africa when complemented by renewable energy expansion and appropriate environmental policies. The study provides policy recommendations for promoting environmentally sustainable digital transformation in Sub-Saharan Africa.

Keywords: *carbon emissions; digitalization; environmental sustainability; renewable energy; Sub-Saharan Africa*

INTRODUCTION

Human-induced climate change remains one of the most formidable challenges to sustainable development in the twenty-first century. Even as global deployment of clean energy technologies is accelerating, carbon dioxide (CO_2) emissions have hit a new peak of around 37.8 billion tonnes in 2024 (International Energy Agency, 2024). Lowering carbon intensity has been a stubborn challenge, and progress toward climate targets has fallen short of the necessary pace. Developing countries are especially burdened in this regard. Despite the relatively small amount of cumulative historical emissions from Sub-Saharan Africa (SSA), the countries in the region are already facing disproportionate climate impacts, such as worsening heat extremes, lengthening dry spells, and more frequent and severe floods (IPCC, 2022). Entrenched structural development problems exacerbate these. It is in this context that there is a high policy priority in identifying credible drivers of emission reductions in SSA.

Digitalisation, in its broad sense, defined as the diffusion and embedding of information and communication technologies (ICT) in economic and social systems, has become one of the new factors potentially shaping the future. In the past 20 years, SSA has seen tremendous growth in the digital infrastructure. The proliferation of mobile broadband and governments' digital agendas, such as the African Union's Digital Transformation Strategy for Africa (2020-2030), Rwanda's Vision 2050, Kenya's National Digital Economy Blueprint, and Nigeria's National Digital Economy Policy, have been the major factors fueling this growth. The share of the population with access to the internet increased from almost zero in the early 2000s to around 37% in 2023. Mobile subscriptions now extend to over 40% of the population, making mobile connectivity the primary gateway to digital participation across the region (GSMA, 2023; ITU, 2023). At the same time, SSA's CO_2 emissions have been on a steady upward trajectory (Ritchie, 2024). This is due to rapid population growth, ongoing urbanisation, growing industrialisation and continued reliance on fossil fuel energy systems (World Bank, 2023). This bi-directional relationship poses a policy problem: can ICT development be a useful tool for achieving environmental sustainability in sub-Saharan Africa?

SSA presents a structurally distinct context that sets it apart from other regions studied in the literature. The IEA reports show that inadequate electricity access in 2023 represents the highest concentration of energy poverty globally. This deficit forces mobile towers and data centres to rely on diesel generators and directly couples ICT expansion to fossil fuel consumption (IEA, 2023). Compounding this, broadband quality remains severely limited despite rapid growth in mobile subscriptions, constraining the substitution and efficiency effects through which ICT can reduce emissions (ITU, 2023). The dominance of informal sectors and subsistence agriculture further narrows the productivity and dematerialisation pathways through which digital connectivity generates environmental dividends in more formalised economies (Avom et al., 2020). Beyond the digital dimension, biomass dominates in the energy consumption system in many SSA countries while renewable energy penetration remains limited in scope and scale (World Bank, 2023). These structural realities suggest that ICT-emission dynamics in SSA are likely to differ substantially from patterns documented in high-income or Asian economies.

The theoretical channels through which ICT influences CO_2 emissions are multidirectional and context-dependent. The literature has yet to reach a settled consensus on the net environmental effect. On one hand, digital technologies can support environmental sustainability through smart grid management, telecommuting, precision agriculture, and the dematerialisation of goods and services. These are collectively described as the optimisation and substitution effects (Asongu, 2018; Asongu et al., 2018). Ren et al. (2023) find that internet development reduces environmental pollution in China, operating through technological innovation, industrial upgrading, and human capital accumulation. Charfeddine et al. (2024) examine the world's most polluted countries and demonstrate that a composite digitalisation index exerts a consistently positive effect on environmental quality even when individual ICT indicators yield mixed results. In addition, Adeshola et al. (2024) reveal that ICT plus environmental taxes can significantly cut down on GHGs, especially when a meaningful threshold of digital penetration is reached.

However, ICT hardware manufacturing, operation, and disposal require significant amounts of Energy and electronic waste. Expansion of the digital domain also fosters consumption trends that can increase emissions via the rebound effect (Kunkel & Tyfield, 2021; Lange et al., 2020). Bieser and Hilty (2018) claim that digitalisation can improve efficiency, but it is often accompanied by induced production and consumption. In an empirical analysis on the UK, Zulfiqar et al. (2023) show that internet consumption has a negative impact on ecological footprints. However, mobile and fixed telephone subscriptions have a positive impact on carbon emissions when energy consumption is rising. This highlights how the energy mix moderates the ultimate environmental outcome of digital expansion.

The relationship between digitalisation and CO_2 emissions is further Complicated by evidence of a nonlinear impact. Saia (2023) utilised a panel smooth transition regression across 55 economies and found that the effect of digitalisation on emissions transitions from positive to negative once a country's R&D output surpasses a critical threshold. This is consistent with an Environmental Kuznets Curve (EKC) dynamic in which early-stage ICT adoption initially raises emissions before efficiency effects eventually dominate. Kwilinski (2024) similarly found a nonlinear pattern across the EU countries where there exists a decreasing marginal benefit of emissions reductions from digital technology improvement for countries with larger improvements. For OECD countries, Ullah et al. (2024) show that technological innovation and digitalisation boost carbon emissions in the short run while financial innovation poses a negative effect. The combined results indicate that the environmental merits of ICT depend on an economy's innovation potential, institutional performance and energy structure.

A substantial body of evidence suggests that digitalisation contributes to environmental sustainability by reducing carbon emissions through efficiency gains, technological innovation, and digital substitution. For instance, Zhao et al. (2021), Andlib and Khan (2021), and Ramos-Meza et al. (2021) find that internet and mobile penetration reduce long-run carbon intensity in Asian and South Asian economies, where governance quality and green globalisation dynamics amplify the digital-environmental dividend. Corroborating evidence from Africa is provided by Amowine et al. (2025) and Wei et al. (2024), who find that digitalisation reduces carbon efficiency and CO_2 intensity, respectively. In contrast, another strand of the literature reports that ICT increases CO_2 emissions, particularly where digital expansion is accompanied by higher electricity demand and carbon-intensive energy consumption. Avom et al. (2020) show that ICT raises CO_2 emissions in 21 SSA countries through energy consumption and financial development channels, while Thierry et al. (2022) report similar detrimental effects across 38 SSA countries. A more nuanced pattern also emerges, highlighting how effects vary by ICT dimension. Villanthenkodath et al. (2021) and Emous and Krušinskas (2026) also find that internet penetration reduces emissions while mobile subscriptions raise them, reflecting the heterogeneous energy intensity of different digital technologies. Overall, the direction and magnitude of the ICT-CO_2 relationship are shaped by ICT proxy selection, energy structure, and whether bidirectional feedback is explicitly modelled.

Notwithstanding, critical gaps remain in the literature on Sub-Saharan Africa. While most empirical evidence is drawn from high-income economies, China, or global panels, the limited SSA studies also exhibit important methodological shortcomings. For example, Avom et al. (2020) and Thierry et al. (2022) rely primarily on single ICT indicators, which may not adequately capture the multidimensional nature of digitalisation in a region where mobile connectivity dominates but broadband access remains limited. As noted by Charfeddine et al. (2024), composite digitalisation indices provide a more comprehensive measure of digital transformation than individual ICT proxies. In addition, existing SSA studies have paid limited attention to panel data challenges arising from cross-country interdependence and structural heterogeneity, which can bias conventional estimators. They have also largely overlooked the potential bidirectional relationship between ICT and CO_2 emissions. This study addresses these gaps by constructing a PCA-based composite ICT index, employing estimation techniques that account for cross-sectional dependence and slope heterogeneity, and examining bidirectional causality using the Dumitrescu–Hurlin heterogeneous panel Granger causality approach.

This study addresses those gaps through four specific contributions. First, a composite ICT index is constructed via PCA, combining internet usage and mobile subscriptions. Second, a rigorous battery of second-generation diagnostic tests is applied prior to estimation. Third, a dynamic two-way fixed effects

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estimator is adopted to account for country-specific and time-specific heterogeneity and emission persistence. Fourth, the Dumitrescu-Hurlin panel Granger causality test is applied to formally examine the direction of causality between ICT and CO_2 emissions. This approach provides novel evidence on feedback dynamics that the existing SSA literature has yet to address systematically.

MATERIALS AND METHODS

1. Data and Sample

This study examines the impact of digitalisation on environmental quality in Sub-Saharan Africa, using a panel dataset of 41 countries over the period 2004–2023. This period was selected because consistent and complete data for all study variables are available across this sample of Sub-Saharan African countries. The panel approach is adopted because it exploits both cross-sectional and time-series variation, controls for unobserved country-specific heterogeneity, and accommodates the structural diversity that characterises SSA economies (Baltagi, 2021). CO_2 emissions are log-transformed to reduce skewness and stabilise variance. All remaining variables are retained in their original units.

2. Variable Description

Table 1 summarises all variables, symbols, measurements, and data sources used in the analysis.

Table 1. Variable Description

Variable	Symbol	Measurement	Source
CO_2 Emissions	lnco2	Log of CO_2 emissions per capita (metric tons)	WDI
Internet Usage	in_inta	Individuals using the internet (% population)	ITU
Mobile Subscriptions	msc	Mobile subscriptions per 100 people	ITU
ICT Index	ict_index	PCA-based ICT composite index	Author
Economic Growth	gdp_an	Annual GDP growth (%)	WDI
Renewable Energy	rewc	renewable energy consumption (%)	WDI
Trade Openness	top	Exports + Imports (% GDP)	WDI
FDI	fdi	Net FDI inflows (% GDP)	WDI

Note: WDI = World Development Indicators (World Bank); ITU = International Telecommunication Union. The ICT Index is author-constructed via PCA.

Source: World Bank WDI; ITU; Authors' computation of ICT Index

CO_2 emissions per capita serve as the primary indicator of environmental quality, consistent with the ICT-environment literature (Asongu, 2018; Avom et al., 2020; Charfeddine et al., 2024). Digitalisation is proxied through three complementary measures, such as internet usage, mobile subscriptions, and a composite ICT index to capture the multidimensional nature of digital development (Charfeddine et al., 2024; Emous & Krušinskas, 2026).

This study identifies four control variables based on established theoretical and empirical foundations. GDP growth captures economic scale effects, as expanding economies raise industrial output, energy demand, and transport emissions, consistent with the Environment Kuznets Curve scale effects (Saia, 2023; Ullah et al., 2024). Renewable energy consumption represents the most direct pathway to emission reduction through the substitution of fossil fuels with clean energy sources (Amowine et al., 2025; Zoundi, 2017). Trade openness captures the pollution haven hypothesis whereby economic integration may relocate carbon-intensive production to regions with weaker environmental regulation (Essandoh et al., 2020; Ramos-Meza et al., 2021). FDI tests whether foreign capital generates pollution halo or pollution haven effects in SSA's resource-intensive economy (Avom et al., 2020). Several variables are intentionally excluded. Total energy consumption is omitted because renewable energy already captures the primary energy-mix channel, and the joint inclusion would introduce multicollinearity. Urbanisation and industrialisation operate indirectly through GDP and energy consumption, which are already controlled, making their inclusion redundant and potentially endogenous. Population density and institutional quality exhibit limited within-country time variation and are absorbed by country fixed effects.

3. Construction of the Composite ICT Index

A composite ICT index is constructed using Principal Component Analysis (PCA) to address the high intercorrelation between internet usage and mobile subscriptions ($r = 0.745$). PCA is a dimensionality-reduction technique that extracts orthogonal linear combinations of correlated variables, retaining maximum variance in fewer components (Greene, 2018). It is widely used to construct composite indices where individual indicators are highly correlated (Charfeddine et al., 2024; Tram et al., 2023). Both ICT variables are standardised (z-scored) before the PCA to ensure scale comparability.

Table 2 presents the PCA results. The Kaiser-Meyer-Olkin (KMO) statistic yields an overall value of 0.500, which meets the minimum acceptable threshold attributable to the two-variable structure of the index (Kaiser, 1974). The first principal component (Comp1) has an eigenvalue of 1.745 and explains 87.23% of the total variance, well above the Kaiser criterion of 1.0. Both variables load equally on Comp1 with eigenvector weights of 0.7071, confirming symmetric weighting. The scores from Comp1 are retained as the composite ICT index.

Table 2. Principal Component Analysis (PCA) for ICT Index Construction

Statistics	**Comp1**	**Comp2**	
Eigenvalue	1.745	0.255	
Proportion of Variance	0.8723	0.1277	
Cumulative Proportion	0.8723	1.0000	
Factor Loadings (Eigenvectors)			
Variable	**Comp1**	**Comp2**	**KMO**
Internet Usage (z_internet)	0.7071	0.7071	0.500
Mobile Subscriptions (z_msc)	0.7071	−0.7071	0.500
Overall KMO	—	—	**0.500**

Note: PCA conducted on standardised variables. KMO = 0.500 meets the minimum threshold (Kaiser, 1974). Component 1 was retained based on the Kaiser criterion (eigenvalue > 1), explaining 87.23% of total variance.

Source: Authors' own computation using STATA 17

4. Diagnostic Tests

A sequence of pre-estimation diagnostic tests is conducted to validate the empirical strategy and guide estimator selection.

a. Multicollinearity. The Variance Inflation Factor (VIF) test is applied first (**Table 3**). All VIF values fall well below the conventional threshold of 10, with a mean VIF of 1.25, confirming the absence of severe multicollinearity.

Table 3. Variance Inflation Factor (VIF) Test for Multicollinearity

Variable	VIF	Tolerance (1/VIF)
Renewable Energy (rewc)	1.54	0.6498
ICT Index (ict_index)	1.36	0.7346
Trade Openness (top)	1.26	0.7925
GDP Growth (gdp_an)	1.05	0.9482
FDI (fdi)	1.01	0.9874
Mean VIF	**1.25**	—

Note: All VIF values are below the threshold of 10. Mean VIF = 1.25, confirming no severe multicollinearity.

Source: Author's own computation using STATA 17

b. Cross-Sectional Dependence. Cross-sectional dependence (CSD) arises when panel units share common shocks or spatial spillovers. Ignoring CSD produces biased and inconsistent estimates (De Hoyos & Sarafidis, 2006; Pesaran, 2021). Two tests are applied in the form of the Pesaran (2021) CD test and the Breusch and Pagan (1980) LM test to confirm CSD.
c. Slope Homogeneity. The Pesaran and Yamagata (2008) delta test examines whether slope coefficients are homogeneous across panel units. Rejecting homogeneity confirms country-specific heterogeneity in the ICT–emission relationship.
d. Model Specification. The Hausman (1978) test is used to choose between fixed and random effects. The modified Wald test detects groupwise heteroskedasticity, and the Wooldridge (2002) test examines first-order serial correlation.

5. Empirical Model

The basic model takes the form of a dynamic two-way fixed effects model shown in equation 1.

$$\ln CO_{2it} = \alpha + \beta_1 \ln CO_{2i,t-1} + \beta_2\, ICT_{it} + \beta_3\, GDP_{it} + \beta_4\, REWC_{it} + \beta_5\, TOP_{it} + \beta_6\, FDI_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

where i and t denote country and year; $\ln CO_{2i,t-1}$ is the lagged dependent variable capturing emission persistence; ICT_{it} is alternatively internet usage, mobile subscriptions, or the composite

ICT index; μ_i and λ_t are country and year fixed effects; and ε_{it} is the idiosyncratic error term. Three separate specifications are estimated for the ICT proxy.

a. Justification for the Dynamic Two-Way Fixed Effects Estimator

The choice of the dynamic TWFE estimator is motivated by several diagnostic findings. First, the Hausman (1978) test rejects the random effects specification in favour of fixed effects ($\chi^2 = 27.27$, $p < 0.001$). Second, the confirmed presence of heteroskedasticity, serial correlation, cross-sectional dependence, and slope heterogeneity necessitates country-clustered robust standard errors for consistent inference (Cameron & Miller, 2015; Wooldridge, 2002). Third, the lagged dependent variable accounts for the persistence of CO_2 emissions over time. Studies such as Asongu et al. (2018), Zhao et al. (2021), and Andlib and Khan (2021) adopt similar dynamic fixed effects frameworks for CO_2 modelling in heterogeneous developing country panels.

6. Granger Causality Test

The Dumitrescu and Hurlin (2012) panel Granger causality test is applied to examine the direction of causality between ICT and CO_2 emissions. Unlike conventional Granger tests, this procedure is designed for heterogeneous panels and does not impose homogeneous slope coefficients across countries. It reports the W-bar, Z-bar, and small-sample-corrected Z-bar tilde statistics, and allows for the detection of bidirectional causality.

7. Robustness Checks

Several procedures verify the stability of baseline findings. First, internet usage, mobile subscriptions, and the composite ICT index are estimated in separate model specifications; consistency across all three proxies confirms insensitivity to the choice of ICT measure. Second, the Dumitrescu-Hurlin Granger causality test provides additional evidence on the dynamic ICT–CO_2 relationship beyond the regression results.

RESULTS AND DISCUSSION

1. Descriptive Statistics and Correlation Analysis

Table 4 presents the descriptive statistics for all variables. The mean log CO_2

emission of −1.021 reflects SSA's generally low emission levels relative to global averages, yet the large standard deviation (1.219) reveals profound cross-country heterogeneity in emission intensities. This variation explains the region's wide differences in economic structure, energy dependence, and levels of industrialisation, ranging from resource-intensive economies to predominantly agrarian countries. Similarly, the ICT index exhibits considerable dispersion (SD = 1.237), highlighting uneven digital development across SSA. While some countries have made significant progress in digital infrastructure and internet penetration, others continue to face limited connectivity and unreliable electricity supply. Internet usage averages only 15.97% of the population despite relatively high mobile subscriptions (61.45 per 100 people), underscoring that mobile connectivity has expanded more rapidly than broadband-based digital adoption (GSMA, 2023; ITU, 2023). These differences reinforce the heterogeneous nature of the SSA region and justify the use of a panel estimation approach with country-specific effects to account for unobserved cross-country differences. The Jarque-Bera test rejects normality for all variables at the 1% level and therefore justifies the log transformations applied.

Table 4. Descriptive Statistics

Stats	$lnCO_2$	ICT Index	Mobile Sub	Internet Use	GDP Growth	Renewable	Trade Open	FDI
Mean	−1.021	−0.115	61.445	15.967	4.151	4.033	57.802	4.270
Max	2.256	4.257	179.027	81.360	37.999	4.584	165.049	103.337
Min	−3.717	−1.728	0.204	0.000	−36.392	1.308	0.000	−17.292
Std. Dev.	1.219	1.237	40.104	17.711	4.844	0.652	35.599	7.807
Skewness	0.372	0.934	0.464	1.493	−1.026	−1.998	0.285	6.549
Kurtosis	2.981	3.523	2.586	4.730	17.783	6.666	2.925	66.907
Jarque-Bera	16.06***	76.24***	30.18***	160.95***	223.36***	230.09***	10.36***	778.33***

Note: ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively. Jarque-Bera statistics test for normality.

Source: Authors' computation via STATA 17. Data from World Bank WDI and ITU

Figure 1 illustrates the trend in CO_2 emissions across Sub-Saharan Africa during the study period (2004–2023). As shown, emissions generally increased

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over the period, highlighting the growing environmental challenge that motivates this study.

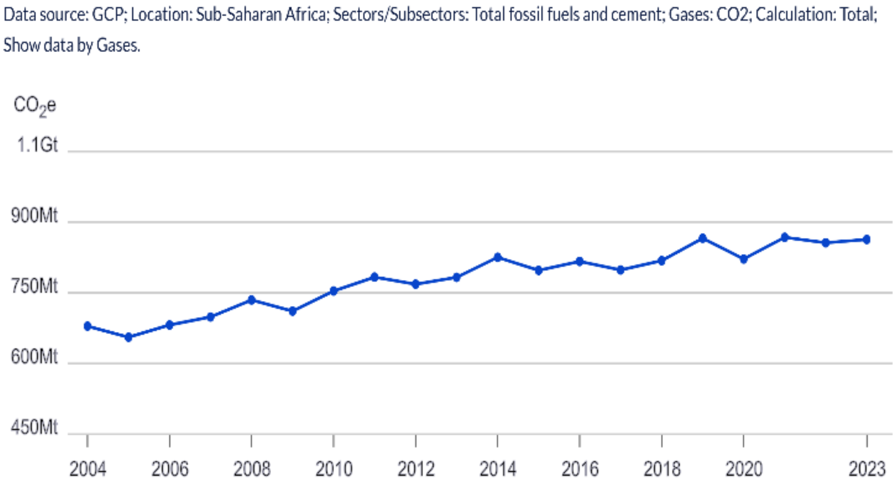

Figure 1. CO_2 Emissions Trends in Sub-Saharan Africa, 2004–2023.

Source: Climate Watch / Global Carbon Project (GCP), 2023

Table 5 presents the correlation matrix. All three ICT measures are positively and significantly correlated with CO_2 emissions. Renewable energy consumption shows the strongest negative correlation with CO_2 (−0.811). Internet usage and mobile subscriptions are highly intercorrelated (r = 0.745), confirming the rationale for constructing a composite ICT index via PCA.

Table 5. Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) lnCO₂	1.000							
(2) ICT Index	0.557***	1.000						
(3) Mobile Sub	0.517***	0.938***	1.000					
(4) Internet Use	0.523***	0.930***	0.745***	1.000				
(5) GDP Growth	−0.131***	−0.180***	−0.153***	−0.185***	1.000			
(6) Renewable	−0.811***	−0.486***	−0.402***	−0.513***	0.126***	1.000		
(7) Trade Open	0.406***	0.268***	0.276***	0.224***	−0.022	−0.452***	1.000	
(8) FDI	0.017	−0.057*	−0.034	−0.074**	0.089**	−0.016	0.040	1.000

Note: ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Source: Author's own computation using STATA 17.

2. Pre-Estimation Diagnostic Tests

A rigorous battery of diagnostic tests is conducted prior to estimation to guide estimator selection and safeguard against biased inference. **Table 6** reports the cross-sectional dependence (CD) test results. Both the Pesaran (2021) CD test and Breusch-Pagan (1980) LM test reject the null hypothesis of cross-sectional independence for all variables at the 1% level. CD statistics range from 5.16 (FDI) to 120.64 (ICT index). This confirms that SSA countries are subject to common shocks reflecting shared exposure to global commodity cycles, regional climate events, and coordinated international development policies, as De Hoyos and Sarafidis (2006) argue that ignoring cross-sectional dependence leads to severely biased estimates.

Table 6. Cross-Sectional Dependence Test Results

Test	CO_2	ICT Index	GDP Growth	Renewable	Trade Open	FDI
Pesaran CD	28.94***	120.64***	25.40***	48.40***	5.31***	5.16***
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Breusch-Pagan LM	5625.31***	14609.86***	1984.59***	5441.52***	2783.88***	1479.46***
p-value	0.000	0.000	0.000	0.000	0.000	0.000

Note: ***, **, and * indicate significance at 1%, 5%, and 10% levels. CD test follows Pesaran (2021); LM test follows Breusch and Pagan (1980).

Source: Author's own computation using STATA 17.

Table 7 presents the Pesaran and Yamagata (2008) slope homogeneity test results. Both the delta (Δ = 15.198) and adjusted delta ($\tilde{\Delta}$ = 19.238) statistics reject the null of homogeneous slopes at the 1% significance level. This confirms meaningful cross-country heterogeneity in the emission–ICT relationship and rules out pooled estimation strategies.

Table 7. Pesaran-Yamagata Slope Homogeneity Test

Test Statistic	Value	p-value
Delta (Δ)	15.198***	0.000
Adjusted Delta ($\tilde{\Delta}$)	19.238***	0.000

Note: *** indicates rejection of homogeneous slopes at the 1% level. Follows Pesaran and Yamagata (2008), Journal of Econometrics, 142(1), 50–93.

Source: Author's own computation using STATA 17.

Table 8 summarises the remaining diagnostics. The modified Wald test rejects homoskedastic errors (χ^2 = 5403.05, $p < 0.001$). The Wooldridge (2002) test rejects no serial correlation ($F = 142.98$, $p < 0.001$). The Hausman (1978) test favours fixed over random effects ($\chi^2 = 27.27$, $p < 0.001$). Together, these confirm that a dynamic two-way fixed effects estimator with country-clustered robust standard errors is the most appropriate estimation strategy.

Table 8. Model Diagnostic Test Results

Test	Null Hypothesis	Statistic	p-value
Modified Wald (χ^2)	Homoskedasticity	5403.05***	<0.001
Wooldridge Test (F)	No Serial Correlation	142.98***	<0.001
Hausman Test (χ^2)	RE is consistent	27.27***	<0.001

Note: *** indicates rejection of the null at the 1% level. Heteroskedasticity follows Greene (2000); serial correlation follows Wooldridge (2002); specification test follows Hausman (1978)

Source: Author's own computation using STATA 17.

3. Main Regression Results

Table 9 presents the dynamic two-way fixed effects estimation results across three model specifications. The R-squared values of 0.747, 0.741, and 0.746 indicate that approximately 74-75% of within-country variation in CO_2 emissions is explained by the models, a strong fit for a heterogeneous panel of 41 countries.

Emission Persistence. The lagged CO_2 coefficient is positive and highly significant across all three models, ranging from 0.799 to 0.818, indicating that approximately 80% of the previous year's emissions persist into the current year. This confirms the strong structural inertia of carbon emissions in Sub-Saharan Africa, reflecting the region's continued dependence on carbon-intensive energy systems and slow transition to cleaner technologies. The finding is consistent with the energy-system path dependence documented by Asongu et al. (2018) and Zhao et al. (2021). It implies that emission-reduction policies in SSA will take several years to yield measurable results. Instead, sustained investments in clean Energy, digital infrastructure, and low-carbon technologies are required to alter the region's long-term emissions trajectory gradually.

Table 9. Dynamic Two-Way Fixed Effects Estimation Results

Variable	Model 1: Internet	Model 2: Mobile	Model 3: ICT Index
Lagged CO_2	0.799*** (0.037)	0.818*** (0.036)	0.812*** (0.036)
Internet Usage	−0.0019** (0.001)	—	—
Mobile Subscriptions	—	−0.0002 (0.0000)	—
ICT Index	—	—	−0.0278** (0.013)
GDP Growth	0.0055*** (0.001)	0.0056*** (0.001)	0.0058*** (0.001)
Renewable Energy	−0.218*** (0.076)	−0.208*** (0.069)	−0.215*** (0.076)
Trade Openness	0.0006* (0.0000)	0.0006** (0.000)	0.0006** (0.000)
FDI	0.0014*** (0.000)	0.0015*** (0.000)	0.0015*** (0.000)
Constant	0.653** (0.2880)	0.607** (0.2580)	0.618** (0.2840)
Observations	820	820	820
Within R^2	0.747	0.741	0.746

Note: Standard errors in parentheses, clustered at the country level. Country and year fixed effects are included in all models. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Source: Author's own computation using STATA 17.

Digitalisation and CO_2 Emissions. The results reveal that digitalisation reduces CO_2 emissions in two of the three specifications. In Model 1, a one percentage point increase in internet usage reduces log CO_2 emissions by 0.0019 ($p < 0.05$). In Model 3, a one-unit increase in the composite ICT index reduces log CO_2 emissions by 0.0278 ($p < 0.05$). The statistically significant coefficients of the composite index indicate digitalisation contributes meaningfully to environmental sustainability by improving resource efficiency and supporting lower-carbon economic activities. These benefits are likely to be more pronounced in countries with relatively better electricity access and digital infrastructure. In contrast, economies that remain heavily dependent on fossil fuels and traditional biomass may experience more limited environmental gains. Moreover, differences in economic development across SSA countries imply that the environmental returns to digitalisation are unlikely to be uniform throughout the region. These findings are consistent with Asongu (2018), Ren et al. (2023), and Andlib and Khan (2021), who document an emissions-reducing effect of internet-based digitalisation across developing economies.

Mobile subscriptions in Model 2, however, are negative but statistically insignificant. This result is not unexpected. In SSA, a substantial proportion of mobile subscriptions remain limited to basic voice calls and SMS services, with limited broadband data capability reducing the substitution and efficiency potential that drives emissions reduction (GSMA, 2023). Furthermore, considerable disparities in digital development across SSA countries imply that mobile connectivity alone is insufficient to deliver measurable environmental improvements without complementary investments in reliable electricity, broadband infrastructure, and digital capabilities. The high correlation between internet usage and mobile subscriptions ($r = 0.745$) further explains that when their shared variance is pooled into the composite ICT index, the environmental effect becomes statistically cleaner and more precisely estimated (Charfeddine et al., 2024). The composite index result should therefore be regarded as the most reliable representation of the overall digitalisation effect in this study.

In contrast, Avom et al. (2020) find that ICT significantly increases CO_2 emissions through its effects on energy consumption. Thierry et al. (2022) similarly report that ICT worsens environmental quality in 38 SSA countries. These contrasting findings reflect differences in sample periods, estimation techniques, and the use of single ICT indicators rather than a multidimensional measure of digitalisation.

From a policy standpoint, these findings carry clear implications. Expanding broadband internet access should be prioritised within digital transformation agendas. Policies such as infrastructure subsidies, public Wi-Fi programmes, and regulatory reforms that reduce broadband costs can accelerate the emissions-reduction effect identified here. Integrating ICT expansion with renewable energy deployment can further amplify the environmental dividend of digitalisation. The results also support the African Union's Digital Transformation Strategy as a climate-compatible development pathway provided that it explicitly incorporates environmental sustainability objectives.

Renewable energy consumption is negative and highly significant across all three models, confirming that expanding the share of renewables in the energy mix is a direct pathway to emissions reduction. Where many SSA countries continue to rely heavily on fossil fuels and traditional biomass, expanding access to renewable energy offers substantial potential to decouple economic development from carbon emissions. This is consistent with Amowine et al. (2025) and Zhao et al. (2021) and underscores the complementarity between renewable energy deployment and digitalisation.

GDP growth, trade openness, and FDI all exert positive and significant effects on CO_2 emissions, suggesting that current patterns of economic expansion in Sub-Saharan Africa remain associated with higher carbon emissions. The significant positive coefficients imply that, without stronger environmental safeguards, continued economic integration and investment may intensify pressure on the region's environment. This finding reflects the structural characteristics of many SSA economies, where industrialisation, trade expansion, and foreign investment continue to be closely linked to carbon-intensive production and fossil fuel-based energy systems. The results are consistent with the pollution haven hypothesis and the early-stage EKC position of most SSA economies (Andlib & Khan, 2021; Ramos-Meza et al., 2021; Saia, 2023). Policymakers should attach environmental conditionalities to trade agreements and FDI frameworks to redirect foreign capital toward low-carbon sectors.

While our findings are robust across multiple ICT specifications and diagnostic frameworks, the study's main limitation is the few number of proxies used to build a digitalization using PCA. The composite ICT index is built from only two indicators due to data constraints across SSA countries; advanced dimensions such as broadband speed, cloud computing, and e-government indices are not incorporated, and their inclusion in future work may yield richer insights. While the diagnostic results support the dynamic Two Way Fixed Effects framework, it does not capture potential nonlinear threshold effects in the ICT–CO_2 relationship. Evidence from Saia (2023) and Kwilinski (2024) suggests that digitalisation's environmental benefits may only materialise above critical R&D or penetration thresholds. The study also does not model spatial spillover effects between SSA countries.

4. Granger Causality Results

Table 10 presents the Dumitrescu and Hurlin (2012) panel Granger causality test results between the ICT index and CO_2 emissions at lag 1.

Table 10. Dumitrescu-Hurlin Panel Granger Causality Test Results

Direction	Lag	W-bar	Z-bar	p-value	Z-bar tilde	Decision
$CO_2 \rightarrow$ ICT	1	1.884	4.001***	0.0001	2.625***	Reject H_0
ICT $\rightarrow CO_2$	1	3.602	11.783***	0.0000	8.715***	Reject H_0

Note: H_0 denotes no Granger causality. *** indicates significance at the 1% level. Follows Dumitrescu and Hurlin (2012), Economic Modelling, 29(4), 1450–1460.

Source: Author's own computation using STATA 17.

The results confirm bidirectional causality between ICT and CO_2 emissions at the 1% significance level in both directions.

The direction ICT $\rightarrow CO_2$ confirms that digital development Granger-causes changes in carbon emissions, consistent with the regression findings (Adeshola et al., 2024; Asongu, 2018; Ren et al., 2023). More novel is the reverse direction of $CO_2 \rightarrow$ ICT, which implies that emission trajectories also influence the pace of digital infrastructure development. Countries with higher emissions are often characterised by fossil fuel dependence, chronic energy insecurity, and weaker institutional capacity. This is consistent with Bieser and Hilty (2018) and Kunkel and Tyfield (2021), who highlight the co-evolutionary nature of digitalisation and environmental sustainability.

The bidirectional result implies that digital policy and climate policy in SSA cannot be designed in isolation. Efforts to expand ICT access will generate downstream environmental benefits but environmental degradation, if unchecked can erode the conditions necessary for sustained digital development. Integrated policy frameworks that link digital transformation agendas to renewable energy deployment and improved environmental governance are therefore essential.

CONCLUSIONS

This study investigates the effect of digitalisation on environmental quality in Sub-Saharan Africa, using panel data from 41 countries over the period 2004–2023. Three ICT proxies are employed within a dynamic two-way fixed effects framework. Our findings consistently show that digitalisation reduces CO_2 emissions, with the composite ICT index and internet usage yielding statistically significant results. Renewable energy consumption further mitigates emissions, while economic growth, trade openness, and FDI are associated with increased carbon intensity. The Dumitrescu-Hurlin Granger causality test asserts that the causal relationship between ICT and CO_2 emissions is bidirectional, thus digitalisation and environmental quality are mutually reinforcing in the SSA context.

This study makes several novel contributions to the literature and policy discourse on digitalization and environmental issues. This study overcomes the limitation of a single-indicator proxy by developing a multidimensional ICT index based on PCA for SSA. In addition, the confirmation of bidirectional causality reveals a feedback dynamic with important implications for the co-design of digital and climate policies. Moreover, the study applies a comprehensive second-generation diagnostic testing framework, ensuring that the estimation strategy is grounded in the actual data structure of the panel.

A clear policy implication would be to prioritise expanding broadband internet access within digital transformation agendas. The environmental dividend of digitalisation can be magnified by integrating digital infrastructure deployment with renewable energy. Trade and FDI policies should incorporate environmental conditionalities to redirect foreign capital toward low-carbon sectors.

This study's limitations are that the analysis is constrained by data availability, particularly the limited coverage of advanced ICT indicators such as fixed broadband speeds and e-government indices. Additionally, the study does not explicitly model the nonlinear or threshold effects of ICT on emissions.

Future studies could explore the threshold and nonlinear effects of digitalisation on environmental quality in SSA. Investigating the moderating role of governance quality, energy structure, and financial development in the ICT–CO_2 relationship could yield more targeted policy insights. Sector-level analysis examining how digitalisation affects emissions in agriculture, industry, and services separately would also provide a more granular understanding of the transmission channels.

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