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THE EFFECT OF INFORMATION AND COMMUNICATION TECHNOLOGY ON ENVIRONMENTALLY SUSTAINABLE DEVELOPMENT IN SUB-SAHARAN AFRICA: THE ROLE OF GREEN INNOVATION AND INDUSTRIAL STRUCTURE

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Abstract

Over the past decades, there have been growing policy and scholarly concerns related to sustainable development in light of growing trends in resource depletion, climate change and environmental degradation. Moreover, such concerns have been documented to be more apparent in sub-Saharan Africa compared to other regions of the world. This study examines the role of green innovation and industrial structure in the relationship between information and communication technologies (ICTs) and environmentally sustainable development in Sub-Saharan Africa (SSA). Utilising data from 41 SSA countries from 1998 to 2022, we employ the ARDL model, PMG estimator, and Granger causality to address methodological challenges. Our findings show that ICT and green innovation are essential for promoting environmental sustainability. Specifically, the results reveal that ICT significantly reduces CO_2 emissions, and investments in green technology also lead to substantial reductions in carbon and methane emissions. However, the industrial structure in SSA countries presents challenges to environmental sustainability. Moreover, the interaction effects between ICT and GDP, as well as between ICT and foreign direct investment (FDI), suggest that integrating ICT with economic growth and FDI can significantly reduce both carbon and methane emissions. Therefore, policymakers are urged to decouple economic growth from environmental degradation by investing in ICT and implementing regulations that encourage sustainable practices among investors.

Keywords: information and communication technologies; environmental sustainability; green technology; industrial structure; Sub-Saharan Africa

1. Introduction

In recent decades, the global discourse on sustainable development has increased due to growing concerns over environmental degradation, climate change, and resource depletion (Musah et al., 2023; Rockström et al., 2009; Steffen et al., 2015). This has shifted attention toward the intersection of economic transformation and environmental sustainability, particularly the role of information and communication technologies (ICTs)–green technology–and industrial structures. The widespread adoption of ICT has revolutionised commerce, communication, and social interactions, offering unique opportunities for economic growth and development (Asongu and Le Roux, 2023; Tchamyou et al., 2023; Brynjolfsson, 2014; Manyika, 2016). However, concerns remain about its environmental impact. Similarly, the adoption of green technology, including innovations aimed at reducing carbon emissions, improving energy efficiency, and promoting sustainable practices, has gained traction as nations transition towards low-carbon economies. Moreover, the structure of industrial activities, shaped by trade dynamics, investment patterns, and policy frameworks, plays a pivotal role in environmental outcomes. Industrial structures, such as dependence on carbon-intensive industries or weak regulatory systems, can hinder progress toward environmental sustainability (Kumar et al., 2017; Smulders and de Nooij, 2003).

Sub-Saharan Africa (SSA) finds itself at a critical juncture in its development trajectory, confronted with the dual challenge of achieving economic growth while addressing pressing environmental concerns. One key factor driving this change is ICT, which has fundamentally transformed human society. ICT significantly supports the development of both advanced and emerging economies (Agboola, 2006; Asongu & Le Roux, 2017). Furthermore, the importance of ICT has expanded beyond a few economic sectors to encompass banking and finance, education, health, energy (Donkor et al., 2022), and various industries (Isiaka et al., 2024). This broadening scope highlights ICT's vital role in promoting sustainable development in the region.

Due to its universal use in advanced nations, ICT's contribution to economic growth cannot be overlooked, yet its impact on environmental pollution is still debated (Manu et al., 2024). The significance of ICT is increasing, and energy consumption related to ICT usage has risen at a rate of 7% per year over the past few decades (Xuezhou et al., 2021). By 2012, global energy consumption due to ICT-related products increased to 4.7%, up from 3.9% in 2007 (Manu et al., 2024). In light of this, the ICT sector's overall contribution to carbon dioxide (CO_2) emissions reached 2% by 2012 (Musah et al., 2023). The ICT industry's share of CO_2 emissions is rising due to pollution from the production of ICT-related materials (Musah et al., 2023) and increased energy demand from the greater use of the internet, mobile devices, and computers (Qalati et al., 2024), which are primary factors in diminishing environmental quality (Cho et al., 2007).

Most research examining the adverse effects of ICT on the environment has focused on energy usage. The production and widespread use of ICT-related products have contributed to increased energy consumption, with some literature suggesting a favorable impact of this consumption on environmental pollution (Chien et al., 2021; Cho et al., 2007). Other studies, such as those by Chenran et al. (2019) and Danish et al. (2018), have examined the positive effects of ICT on environmental quality, arguing that increased ICT use enhances energy sector efficiency and reduces CO_2 and other greenhouse gas emissions. Consequently, while ICT products impact CO_2 emissions, it remains unclear whether this impact is predominantly positive or negative.

Most prior research on the nexus between ICT and CO_2 emissions has focused on developed economies, which accounted for 79% of total emissions between 1850 and 2011 (Manu et al., 2024). However, this trend is shifting, as emerging and developing economies are also contributing to environmental pollution. These countries are responsible for 63% of CO_2 emissions, primarily due to their reliance on excessive mechanization and high energy consumption for economic growth (Bastida et al., 2019).

In this paper, we address the challenges that hinder ICT–green technology–industrial structure in SSA, recognizing the different resource endowments, economic development levels, and manufacturing practices that can affect environmental outcomes. Previous studies have primarily focused on developed nations; however, Africa's diverse regions have not received sufficient attention in this context. Understanding the unique resource endowments and geographical factors in these regions is essential for determining how ICT–green technology–industrial structure can contribute to achieving environmental sustainability. This approach provides a comprehensive perspective on ICT's potential to mitigate CO_2 emissions. Furthermore, the inclusion of green innovation and industrial structures as intervening variables is based on the argument that while linear additive models provide policy makers with insights into how channels affect the outcome variables, intervening variables provide a non-linear framework with which to assess how the effect of the channels on the outcome variables can be moderated. Within the context of the present study, we argue that in the real world, ICT does not influence environmental outcomes in isolation, not least, because their nexus can be contingent on industrial structures and green innovation policies, as articulated in Section 2.2.3 and Section 2.2.2, respectively.

Our research contributes to the existing literature by integrating multiple factors—ICT, green technology, and industrial structure—rather than focusing on isolated aspects, as seen in previous studies (Asiedu et al., 2023; Opuala et al., 2023). Our findings show that ICT and green innovation are critical for promoting environmental sustainability in SSA, with ICT significantly reducing CO_2 emissions and investments in green technology leading to further reductions. However, the industrial structure in SSA presents challenges to achieving sustainability. Furthermore, we find that the interaction effects between ICT, economic growth, and foreign direct investment (FDI) suggest that combining ICT with economic growth and FDI can significantly reduce both carbon and methane emissions. As a result, policymakers are encouraged to decouple economic growth from environmental degradation by investing in ICT and adopting regulations to promote sustainable investor practices. Employing panel pooled mean group (PMG) and autoregressive distributed lag (ARDL) methods, we rigorously analyse the relationship between ICT, green technology adoption, industrial structure, and environmental sustainability in SSA. The employment of robust statistical techniques, combined with real-world data, lends credibility and reliability to our conclusions. Moreover, we identify a critical research gap related to longitudinal studies that track these dynamics over time. Filling this gap is essential for informing evidence-based policies to support sustainable development in SSA. Through our research, we aim to shed light on the long-term trends and interactions between ICT, green innovation, industrial structure, and environmental sustainability, providing crucial insights for policymakers and stakeholders to address environmental risks better.

The rest of the study is structured as follows: The theoretical review and the testable hypotheses are covered in Section 2, while the data and corresponding methodology are discussed in Section 3. The empirical results are provided in Section 4. The last section concludes with policy recommendations.

2. Literature review

2.1. Theoretical review

Several theories examine the role of ICT in driving environmentally sustainable development. In this study, we incorporate the Internet Growth and Contestable Market Theory (IGCMT) and the Unified Theory of Acceptance and Use of Technology (UTAT). The IGCMT suggests that expanding ICT, especially internet usage, can stimulate economic growth and foster competition, which in turn supports environmental sustainability. The internet lowers investment costs, reduces barriers to entry, and facilitates access to environmental information, thereby promoting sustainable technologies (Asongu et al., 2017; Asongu & Le Roux, 2017). ICT also addresses inefficiencies in managing natural resources by reducing information gaps (Manu et al., 2024).

The UTAT highlights differences in technology adoption and acceptance, driven by individual behavior and intention. According to this theory, individuals' use of technology is influenced by performance expectancy, perceived usefulness, and social factors (Ma et al., 2024; Venkatesh et al., 2003). In the context of environmental sustainability, these factors can impact the uptake of green technologies, with adoption varying across regions and influenced by social norms. Additional research supports the positive link between ICT and sustainable development. Haq et al. (2024) show that broadband and internet usage are positively associated with environmental initiatives. Asongu and le Roux (2023) and Asongu and Odhiambo (2022) observe that in SSA, mobile-based applications have led to more efficient resource management, reducing environmental impact through increased mobile technology use.

Claus and Grimes (2003) present two key concepts: transforming risk and optimizing resource allocation. These views reinforce ICT's role in reducing costs and enhancing the flow of environmental information, promoting better resource utilization. ICT reduces operational costs (Muto & Yamano, 2009) and lessens information asymmetry (Aminuzzaman et al., 2003), making it a critical tool in advancing sustainability, especially in developing regions.

2.2 Empirical literature and testable hypotheses

2.2.1 the ICT–environmentally sustainable development nexus

The ICT-environmental sustainability nexus has burgeoned in recent years. Studies have investigated various dimensions of this relationship, highlighting both the positive and negative environmental impacts of ICT use. Studies have identified several ways in which ICT can contribute to environmental sustainability. For instance, ICT enables the optimisation of resource use through smart grids, intelligent transportation systems, and precision agriculture

(Geng et al., 2019). Additionally, ICT facilitates the transition to a circular economy by enabling the sharing and reuse of resources through platforms and digital marketplaces (Geissdoerfer et al., 2017). Conversely, ICT use also poses environmental challenges. The production, use, and disposal of electronic devices contribute to electronic waste (e-waste) generation, posing risks to ecosystems and human health (Di Maio et al., 2017). Moreover, the energy consumption associated with data centers, cloud computing, and high-speed internet infrastructure has raised concerns about carbon emissions and environmental sustainability (Andrae & Edler, 2015).

Studies have explored policy interventions and mitigation strategies to harness the positive aspects of ICT while mitigating its adverse environmental impacts. These include measures to promote eco-design and sustainable manufacturing practices for electronic devices, as well as initiatives to increase energy efficiency in data centers and ICT infrastructure (Paudel et al., 2023). Additionally, research emphasizes the importance of regulatory frameworks and incentives to encourage the adoption of green ICT solutions and promote sustainable consumption patterns (Curtis & Mont, 2020). Studies have also conducted sectoral analyses to understand the environmental implications of specific digital technologies and applications. For example, research has examined the environmental footprint of cloud computing, e-commerce logistics, and digital platforms, highlighting opportunities for improvement through innovation and policy interventions (Hoof et al., 2023; Theuer et al., 2020). Cross-country studies have compared the environmental performance of countries with varying levels of digitalization, providing insights into the complex relationship between ICT development and environmental sustainability. These studies consider factors such as energy consumption, carbon emissions, and waste generation, offering valuable perspectives for policymakers and practitioners (Liu et al., 2023; Sadath & Acharya, 2017; Shen et al., 2023). Based on these studies, we formulate the following hypothesis:

H1: The adoption of ICT in SSA countries is positively associated with improvements in environmental sustainability.

2.2.2 The green technology–environmentally sustainable development nexus

The green technology–environmental sustainability nexus has been explored in empirical literature for its potential to mitigate environmental degradation while fostering sustainable development (African Development Bank Group, 2023; UNEP, 2021). Studies have highlighted the role of renewable energy technologies, such as solar, wind, and hydroelectric power, in reducing carbon emissions and dependence on fossil fuels (IPCC, 2023). Additionally, advancements in energy efficiency technologies for buildings, transportation, and manufacturing processes have been shown to contribute to resource conservation and emissions reduction (Khan & Hou, 2021). Beyond energy, green technologies encompass a wide range of innovations, including sustainable agriculture practices, waste management solutions, and eco-friendly materials, each offering opportunities to address environmental challenges (OECD, 2005). Empirical research has also examined the adoption and diffusion of green technologies across different sectors and regions, identifying barriers and drivers of implementation (Acemoglu, 2009). Policy interventions, such as subsidies, regulations, and technology transfer initiatives, have been evaluated for their effectiveness in promoting the adoption of green technologies and achieving environmental sustainability goals (Stern, 2004).

Overall, empirical studies emphasize the importance of green technology innovation and deployment in transitioning toward a more sustainable and resilient future. Based on these studies, we formulate the following hypothesis:

H2: The integration of green technology initiatives in SSA leads to a significant reduction in environmental degradation and promotes overall environmental sustainability in the region.

2.2.3 The industrial structure–environmentally sustainable development nexus

The industrial structure, characterised by market failures, policy inconsistencies, and structural imbalances, can worsen environmental degradation by encouraging unsustainable production and consumption patterns (Kumar et al., 2017; Smulders & de Nooij, 2003; Mishra, 2025). Studies have identified different industrial structures, including subsidies for polluting industries, lax environmental regulations, and misguided incentives that promote resource depletion and pollution (Barrett, 1994; Goulder, 1995; Kelly & Nembot Ndeffo, 2025). These structural elements frequently lead to market inefficiencies, externalities, and resource misallocation, which undermine efforts to achieve environmental sustainability (Dasgupta et al., 2001; Li et al., 2025). Empirical research has examined the environmental impacts of industrial structures across different sectors and regions, emphasising their detrimental effects on air and water quality, biodiversity, and ecosystem integrity (Grossman & Krueger, 1995; Kahn, 2010; Liu et al., 2025). Policy interventions aimed at addressing industrial structure, such as environmental taxes, emissions trading schemes, and green procurement policies, have been evaluated for their effectiveness in promoting cleaner production and fostering environmental sustainability (Fischer & Newell, 2008; Fullerton & Metcalf, 2001; Ke et al., 2025). Overall, empirical studies underscore the need to address industrial structure as a critical step toward achieving environmental sustainability and fostering green growth. Based on the studies, we formulate the following hypothesis:

H3: Industrial structures, such as lax environmental regulations and subsidies to polluting industries, exacerbate environmental degradation in SSA countries, thereby hindering overall environmental sustainability efforts in the region.

In summary, the relationship between ICT, green technology, and industrial structure plays a crucial role in achieving environmental sustainability in SSA. Studies highlight the dual nature of ICT, offering opportunities for economic growth through ICT-driven innovations while posing environmental risks such as electronic waste generation and energy consumption. Similarly, research underscores the potential of green technologies like renewable energy and sustainable agriculture in mitigating environmental degradation. Yet, challenges remain in their widespread adoption due to barriers and policy gaps. Moreover, industrial structure, including market failures and weak regulations, exacerbate environmental degradation in SSA, necessitating policy interventions such as environmental taxes and emissions trading schemes to promote cleaner production practices. Together, these findings emphasize the need for integrated approaches that harness the benefits of ICT-green technology while addressing industrial structure to achieve environmental sustainability in SSA (Barrett, 1994; Acemoglu, 2009; Rogers, 2008; Fullerton, 2008; Kumar et al., 2017; Ofoeda et al., 2024; Wang et al., 2025).

This paper contributes to the extant literature by tackling the challenges that impede the relationship between ICT, green technology, and industrial structure in SSA, taking into account the varying resource endowments, levels of economic development, and manufacturing practices that can influence environmental outcomes. The sparse literature on Africa, coupled with the continent's distinctive resource endowments and geographical factors for a worthwhile framework to ascertain the role of ICT–green technology–industrial structure in achieving environmental sustainability. Additionally, the inclusion of industrial structures and green innovation as intervening variables is predicated on the claim that, although linear additive models tell policymakers how channels impact the outcome variables, intervening variables offer a non-linear framework that allows them to evaluate how the channels' impact on the outcome variables can be mitigated. In light of the current study, we contend that ICT does not, in and of itself, have an isolated impact on environmental outcomes in the real world. This is due, in part, to the fact that their relationship may depend on industrial structures and green innovation policies discussed in the previous sections.

3. Data and methodology

3.1 Model specification

The main objective of this study is to investigate how the adoption of ICT in SSA is linked to improvements in environmental sustainability, along with the roles of green innovation and industrial structure. Following the analysis in Section 2, we propose a log-linear model to examine the impact of ICT, green technology, and industrial structure on environmental sustainability as apparent in Equation (1):

$$ES_{it} = \alpha_i + \beta(ICT)_{it} + \gamma(GT)_{it} + \delta(IS)_{it} + \mathbf{X}'_{\mathbf{it}}\boldsymbol{\theta} + \varepsilon_{it} \quad (1)$$

where ES_{it} represents the environmental sustainability measured by carbon and methane emissions in country i in time t. α_i is the country-specific intercept. **ICT** represents by ICT goods exports (ICTGE) and imports (ICTGI); this variable captures the role of digital trade in influencing sustainability. **Green Technology (GT)** includes R&D expenditure, patent resident (PR), and patent non-resident (PN), reflecting technological innovation's contribution to environmental outcomes. **Industrial Structure (IS)** is proxied by industry-specific variables, such as the share of GDP from industry (Industry GDP) and other industry-related indicators (Industry current) to account for structural economic factors. $\mathbf{X}'_{\mathbf{it}}$ represents a vector of control variables. θ is the corresponding parameter vector. ε_{it} is the error term.

3.2 Data

In our study involving 41 SSA countries, we avoided employing conventional panel data methods such as pooled OLS, fixed effects, or random effects estimators due to various limitations.[1] These methods do not accommodate the lagged dependent variables as regressors, assume a uniform slope across all units, require variables to be devoid of cross-sectional dependence, have the same order of integration, and encounter challenges in controlling for endogeneity. These constraints could compromise the accuracy of our estimates in Equation (1), which examines the interplay between ICT, green technology, industrial structure, and environmental sustainability. Therefore, we adopted alternative

[1] These countries include Angola, Botswana, Burkina Faso, Burundi, Cape Verde, Cameroon, Central African Republic, Comoros, Democratic Republic of Congo, Republic of Congo, Cote d'Ivoire, Eswatini, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Lesotho, Madagascar, Malawi, Mali, Mauritius, Mozambique, Namibia, Niger, Nigeria, Rwanda, Sao Tome and Principe, Senegal, Seychelles, Sierra Leone, Somalia, South Africa, Sudan, Tanzania, Togo, Uganda, Zambia, Zimbabwe.

strategies to address these concerns and ensure the robustness of our analysis (Aluko & Obalade, 2020; Baltagi, 2008; Christopoulos & Tsionas, 2004; Gasser et al., 2018; Lee et al., 2020).

The discussion underscores the necessity of addressing endogeneity, heterogeneous slopes, lagged dependent variables, cross-sectional dependence, and mixed orders of integration when estimating Equation (1). Hence, we have chosen the panel ARDL model for both theoretical and practical reasons. Theoretically, this model offers more flexibility than other linear estimators, providing consistent and efficient estimates in the presence of cross-sectional dependence and mixed orders of integration (Bildirici, 2014). It also tackles endogeneity by employing an optimal lag structure during estimation (Pesaran, 2021). Practically, the panel ARDL model provides policymakers with valuable insights into the short-run effects and long-run dynamics of ICT in the model (Kapetanios et al., 2011). Since the panel ARDL model falls within the ARDL (*p, q*) family, we convert Equation (1) into a vector error-correction model (VECM) for further analysis as captured in Equation (2):

$$\Delta CO2_{it} = \alpha_i + \theta_i(CO2_{it-1} - \varphi_i'\mathbf{X}_{it}) + \sum_{j=1}^{p-1} \mu_{ij}'\Delta CO2_{it-j} + \sum_{j=0}^{q-1} \delta_{ij}'\Delta\mathbf{X}_{\boldsymbol{it-j}} + \varepsilon_{it} \tag{2}$$

We utilize the first-difference operator (Δ) to capture changes over time. The parameters φ_i' and δ_{ij}' denote the long-run dynamics and short-run effects of the variables, respectively. Of particular interest is the error-correction term (ECT), represented by θ_i., whose magnitude and statistical significance are closely examined. A statistically significant θ_i between 0 and −1 suggests the presence of a cointegrating relationship between carbon and methane emissions and the explanatory variables.

To estimate Equation (2), we employ the PMG estimator, which strikes a balance by accommodating heterogeneity in short-run individual-specific coefficients while maintaining homogeneity in long-run dynamics for consistent results (Zribi & Boufateh, 2020). This feature aligns well with our study's objectives, as long-run homogeneity can stem from advancements in ICT-green technology-industrial structure (Attiaoui et al., 2017), and other factors. Utilizing the PMG estimator allows us to examine the relationship between ICT, green technology, industrial structure, and environmental sustainability, considering the complexities inherent in this relationship. Our adoption of the panel ARDL model and the PMG estimator enables us to mitigate potential issues such as endogeneity, heterogeneous slopes, lagged dependent variables, cross-sectional dependence, and mixed orders of integration that are prevalent in such analyses.

Table 1 provides a comprehensive overview of the statistical summary pertaining to the variables outlined in Equation (1), all of which have been transformed into natural logarithms. Table 1 encapsulates a diverse array of measurements associated with economic and environmental indicators within SSA. Notably, the average carbon emissions within the dataset are recorded at approximately 1.779 units, signifying the quantity of carbon dioxide emitted.

Additionally, methane emissions, another notable contributor to greenhouse gases, exhibit an average value of around 3.463 units. Turning to ICT, denoted by ICTGE and ICTGI, the region demonstrates an average export value of about 0.688 units, juxtaposed with an import of approximately 7.128 units, thus showcasing substantial engagement in ICT trade.

Moreover, the frequency of the sample is contingent upon data availability during the study period on green technology (GT) and patent applications[2]. To handle missing data in the R&D expenditure and patent application variables, we applied a data pre-processing technique using STATA (version 18) software. Specifically, we utilized the 'replace' command with an 'if' condition to fill in missing values with adjacent non-missing values within each group identified by the 'id' variable. This approach maintains data continuity while preserving the dataset's grouping structure. By employing this method, we aimed to mitigate the impact of missing data on our analysis and ensure the robustness of our results. This approach is supported by the observed average R&D expenditure and patent activity—both by residents and non-residents—averaging around 1.686, 0.726, and 0.896 units, respectively. These metrics not only underscore investments in innovation and technological advancement but also signify a thriving ecosystem conducive to intellectual property creation. Additionally, the industrial sector's contribution (IS) to GDP stands at approximately 1.290%, translating to about 1.343 units of GDP. The average GDP for the region is estimated at approximately 3.077 units, with a total population figure of roughly 6.897 units.

Finally, the region's allure to external investors is evidenced by the average foreign direct investment (FDI) of around 1.399 units, illustrating a keen interest from external stakeholders in the economic prospects offered by SSA. Overall, Table 1 provides a glimpse into the economic and environmental landscape of the region, shedding light on key indicators and trends pivotal for understanding SSA's development trajectory.

Table 1. Data and descriptive statistics

Variables	Measurements	Mean	Std. dev.	Min	Max	Sources
CO_2	Carbon emissions	1.779	0.255	0.566	1.993	World Bank
CH4	Methane emission	3.463	0.685	1.446	5.132	World Bank
ICTGE	Information and communication technology goods exports	0.688	0.447	0.002	1.789	World Bank
ICTGI	Information and communication technology goods imports	7.128	0.843	3.697	9.018	World Bank

[2] The STATA (18) command effectively fills in missing data in the R&D expenditure and patent variables by replacing gaps with adjacent non-missing values within each group defined by the "id" variable (bysort id: replace R&D expenditure = R&D expenditure[_n+1] if missing (R&D expenditure)).

R&D	R&D expenditure	1.686	0.492	0.193	2.764	World Bank
PR	Patent resident	0.726	0.624	0.000	3.256	World Bank
PN	Patent non-resident	0.896	0.741	0.000	3.962	World Bank
Indus (GDP)	Industry (including construction), value added (% of GDP)	1.290	0.376	0.034	1.927	World Bank
Indus (current)	Industry (including construction), value added (current LCU)	1.343	0.407	0.025	1.930	World Bank
GDP	GDP	3.077	0.412	2.392	4.224	World Bank
POP	Total population	6.897	0.719	4.897	8.340	World Bank
FDI	Foreign direct investment	1.399	0.392	0.025	1.972	World Bank

Note: World Bank data from World Development Indicators. Std.dev: Standard deviation. Min: Minimum. Max: Maximum.

3.3 Robustness tests

In the previous section, we found that the ICT-green technology-industrial structure have a positive impact on environmental sustainability. However, our analysis assumed a linear relationship between these factors and emissions, potentially overlooking nonlinear effects. To address this, we introduce squared terms for the ICT-green technology-industrial structure as additional variables in the Equation (3) below:

$$ES_{it} = \alpha_i + \beta(ICT)^2_{it} + \gamma(GT)^2_{it} + \delta(IS)^2_{it} + \mathbf{X}'_{\mathbf{it}}\boldsymbol{\theta} + \varepsilon_{it} \quad (3)$$

By including the squared terms of *ICT, GT, and IS*, the equation allows for the examination of potential nonlinear effects on environmental sustainability in SSA.

While we have previously disregarded nonlinearity within the ICT-green technology-industrial structure-emissions relationship, it is plausible that other forms of nonlinearity may exist in Equation (1). To examine this possibility, we turn to two widely recognized hypotheses in environmental economics: the EKC and Pollution Haven Hypothesis (PHH). To test these hypotheses empirically, we introduce the squared terms of GDP and FDI into Equation (1) as follows in Equation (4):

$$ES_{it} = \alpha_i + \beta(ICT)_{it} + \gamma(GT)_{it} + \delta(IS)_{it} + \lambda(GDP)_{it} + \lambda(GDP)^2_{it} + \eta(FDI)_{it} + \eta(FDI)^2_{it} + \mathbf{X}'_{\mathbf{it}}\boldsymbol{\theta} + \varepsilon_{it} \quad (4)$$

Intuitively, if the coefficient λ is positive and the coefficient η is negative. Given that both are statistically significant, it indicates that there is a curved relationship between GDP and emissions, resembling an inverted U-shape. This confirms the EKC. Similarly, if the coefficient ρ is positive and the coefficient v is negative. Since both are statistically significant, it suggests a similar curved relationship between FDI and emissions, supporting the idea of the Pollution Haven Hypothesis (PHH).

So far, we have established the direct impact of ICT-green technology-industrial structure on emissions. Yet, these factors could also indirectly affect emission levels through interaction between green technology and GDP or between green technology and FDI. To consider these mediation effects, we adjust Equation (1) by incorporating an interaction term as follows in Equations (5a) to (5f):

$$CO2_{it} = \alpha_i + \beta(ICT)_{it} + \psi(ICT \times GDP)_{it} + \mathbf{X}'_{\mathbf{it}}\boldsymbol{\theta} + \varepsilon_{it} \tag{5a}$$

$$CO2_{it} = \alpha_i + \beta(ICT)_{it} + \psi(ICT \times FDI)_{it} + \mathbf{X}'_{\mathbf{it}}\boldsymbol{\theta} + \varepsilon_{it} \tag{5b}$$

$$CO2_{it} = \alpha_i + \beta(GT)_{it} + \psi(GT \times GDP)_{it} + \mathbf{X}'_{\mathbf{it}}\boldsymbol{\theta} + \varepsilon_{it} \tag{5c}$$

$$CO2_{it} = \alpha_i + \beta(GT)_{it} + \psi(GT \times FDI)_{it} + \mathbf{X}'_{\mathbf{it}}\boldsymbol{\theta} + \varepsilon_{it} \tag{5d}$$

$$CO2_{it} = \alpha_i + \beta(IS)_{it} + \psi(IS \times GDP)_{it} + \mathbf{X}'_{\mathbf{it}}\boldsymbol{\theta} + \varepsilon_{it} \tag{5e}$$

$$CO2_{it} = \alpha_i + \beta(IS)_{it} + \psi(GT \times FDI)_{it} + \mathbf{X}'_{\mathbf{it}}\boldsymbol{\theta} + \varepsilon_{it} \tag{5f}$$

Equations (5a-b) introduce an interaction term between ICT and GDP (ICT×GDP) and between ICT and FDI (ICT×FDI). This interaction term captures the combined effect of ICT and GDP and ICT and FDI on CO_2 emissions. Equation (5c-d) follows a similar structure as Equation (5) but focuses on the interaction between green technology and GDP (GT×GDP) and between green technology and FDI (GT×FDI). This interaction term captures the combined effect of green technology and GDP and green technology and FDI on CO_2 emissions. The remaining equations (5e-f) extend this approach to include interaction terms between the industrial structure (IS) and GDP (or FDI), denoted as (IS×GDP) or (IS×FDI), respectively. These terms capture the combined impact of the industrial structure and GDP (or FDI) on CO_2 emissions.

4. The Dynamics of ICT, Green Technology, and Industrial Structure on Environmental Sustainability

Table 2 reports the dynamics of ICT, green technology, and industrial structure on environmental sustainability, particularly regarding CO_2 and methane emissions. Firstly, regarding ICT, the statistically significant negative coefficients observed for both exports (ICTGE) and imports (ICTGI) of ICT goods in relation to CO_2 emissions (-0.083 and -0.025) highlight an important trend. It suggests that countries with a more pronounced involvement in either exporting or importing ICT goods tend to exhibit lower levels of CO_2 emissions. The significance levels for these coefficients are at the 5% and 1% levels, respectively. Similarly, for methane emissions, the negative coefficients of ICTGE and ICTGI are also statistically significant at the 1% level (-0.509 and -0.576), suggesting that increased digital economic activities lead to decreased methane emissions, further contributing to environmental sustainability. These values suggest that higher levels of ICT trade are associated with reduced CO_2 and methane emissions within SSA, indicating a positive effect on environmental sustainability. This finding is consistent with studies documenting the transformative impact of ICT, characterized by the widespread adoption of ICTs on global commerce, communication, and social interactions (Asongu & Le Roux, 2023; Brynjolfsson, 2014; Manyika, 2016). These studies emphasize the role of ICT in enhancing efficiency and reducing emissions through digital solutions.

Moving to green technology, investments in research and development (R&D) and resident patents show significant negative coefficients concerning CO_2 emissions (-0.091 and -0.017). These values indicate that higher levels of domestic innovation in green technology are associated with reduced CO_2 emissions within SSA, thus positively impacting environmental sustainability (Chen et al., 2023; Manu et al., 2022). The significance levels for these coefficients are denoted at the 5% level. However, the coefficient for non-resident patents shows a positive relationship with CO_2 emissions (0.008), albeit at a slightly weaker significance level of 10%. This is consistent with literature suggesting that non-resident patents often reflect foreign technologies that may not align with local environmental priorities, as highlighted by Attiaoui et al. (2017).

In terms of industrial structure, while industrial output as a percentage of GDP (Indus GDP) positively influences CO_2 emissions (0.111), the current industrial output (Indus current) negatively affects emissions (-0.041). The significance level for the coefficient of Indus current is denoted at the 5% level. These results suggest that changes in the industrial composition towards less carbon-intensive sectors contribute to lowering CO_2 emissions, thereby positively impacting environmental sustainability in SSA. These findings align with Kapetanios et al. (2011), who noted the importance of structural shifts in reducing emissions in developing economies.

Turning to economic growth, the positive coefficients associated with GDP across various models underscore the significant role of economic growth in driving CO_2 emissions in the region. As GDP increases, so do carbon emissions, reflecting the reliance of SSA countries on carbon-intensive industries for economic development. This suggests that while economic growth is essential for development in SSA, it also poses challenges in terms of environmental sustainability, requiring policymakers to balance economic objectives with environmental concerns. This observation is supported by studies such as those of Manyika (2016), who emphasize the need for green growth strategies in developing economies.

Regarding FDI, the mixed impact observed suggests a refined relationship between foreign investment and CO_2 emissions in SSA. While some models show negative coefficients for FDI, indicating a potential mitigating effect on emissions, others exhibit positive coefficients, suggesting that certain types of foreign investments may contribute to increased emissions. This highlights the need for scrutiny of the types of investments attracted to SSA and the environmental implications they entail. Policymakers should aim to attract green and sustainable investments that promote economic growth while minimizing environmental degradation, a recommendation supported by Chen et al. (2023).

Additionally, the positive coefficients associated with POP indicate that population growth is a significant driver of CO_2 emissions in SSA. As the population increases, so does the demand for goods and services, leading to higher levels of consumption and subsequent carbon emissions. This underscores the importance of addressing population growth alongside economic development to achieve sustainable outcomes in SSA. This finding aligns with the literature, which links demographic pressures to heightened emissions and environmental challenges (Brynjolfsson, 2014).

Turning to methane emissions, GDP, represented by its positive coefficients across various models, indicates a positive association with methane emissions. As GDP increases, methane emissions also tend to rise, suggesting that economic growth contributes to higher levels of methane production, possibly through increased industrial activities, agricultural practices, or energy consumption. This underscores the challenge of balancing economic development with environmental conservation efforts in SSA. On the other hand, the negative coefficients associated with FDI suggest a mitigating effect on methane emissions. Countries receiving higher levels of foreign direct investment tend to exhibit lower methane emissions, indicating that certain types of foreign investments may promote environmentally friendly practices or technologies that reduce methane production. This highlights the potential for foreign investment to contribute positively to environmental sustainability in SSA, provided that investments align with green development objectives (Kapetanios et al., 2011).

Population (POP) also shows a mixed impact on methane emissions, with positive coefficients indicating a positive association in some models and negative coefficients suggesting a mitigating effect in others. The positive association implies that population growth contributes to increased methane emissions, possibly due to higher demand for energy, food production, and waste generation. Conversely, the negative association suggests that population growth may lead to technological advancements or changes in consumption patterns that reduce methane emissions. This underscores the need for comprehensive population management strategies that consider both demographic trends and environmental impacts.

Contextualizing the results for SSA highlights the positive impact of ICT-green technology innovation and shifts in industrial structure on environmental sustainability, particularly regarding CO_2 and methane emissions. Increases in ICT goods, along with investments in green technology research and development, are associated with reduced CO_2 emissions. Moreover, transitions toward less carbon-intensive industrial sectors contribute to lowering CO_2 emissions. However, economic growth, represented by GDP, tends to increase both CO_2 and methane emissions, emphasizing the challenge of balancing development with environmental conservation. Foreign Direct Investment (FDI) shows a mixed impact on emissions, while population growth plays a significant role in driving emissions, especially CO_2. These observations resonate with broader empirical findings that emphasize the complex interplay between economic activities and environmental outcomes in SSA (Chen et al., 2023; Manu et al., 2022).

Table 2. The effects of ICT-green technology-industrial structure on environmental sustainability, by estimator

Dependent var.	Carbon emissions							Methane emissions						
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(a). Long-run dynamics														
ICTGE	-0.083***							-0.509**						
	(0.043)							(0.076)						
ICTGI		-0.025***							-0.576***					
		(0.051)							(0.118)					
R&D			-0.091**							-0.782**				
			(0.061)							(0.270)				
Patent resident				-0.017**							0.086**			
				(0.086)							(0.045)			
Patent non-resident					0.008**							0.147***		
					(0.011)							(0.029)		
Indus $_{(GDP)}$						0.007**							0.111	
						(0.012)							(0.095)	
Indus $_{(current)}$							-0.041**							-0.450**
							(0.017)							(0.240)
GDP	0.033***	0.050***	0.032*	0.192**	0.001**	0.130**	0.141*	0.085**	0.138**	0.116**	0.068	-0.305*	-0.101**	-0.030
	(0.007)	(0.010)	(0.018)	(0.076)	(0.096)	(0.082)	(0.060)	(0.030)	(0.042)	(0.039)	(0.115)	(0.179)	(0.030)	(0.026)
FDI	-0.032	-0.200**	0.019**	0.008**	0.018**	0.044**	-0.428***	-0.116**	-0.127*	-0.183**	-0.105**	0.074**	0.060***	0.054***
	(0.026)	(0.067)	(0.012)	(0.017)	(0.033)	(0.044)	(0.116)	(0.087)	(0.071)	(0.116)	(0.319)	(0.025)	(0.015)	(0.015)
POP	0.500**	0.388**	1.467***	4.293*	0.099**	0.500**	0.388**	0.467***	0.293**	0.056**	0.045**	0.027**	0.261**	0.024**
	(0.619)	(0.399)	(0.785)	(2.007)	(0.065)	(0.619)	(0.399)	(0.785)	(2.007)	(0.018)	(0.013)	(0.017)	(0.086)	(0.068)
(b). Short-run effects														
ECT	**-0.062**	**- 0.029*****	**- 0.031*****	**- 0.055****	**- 0.044****	**-0.011****	**- 0.058*****	**- 0.063*****	**- 0.037*****	**-0.088****	**-0.072****	**-0.080*****	**- 0.093*****	**-0.040***
	(0.066)	**(0.035)**	**(0.231)**	**(0.034)**	**(0.048)**	**(0.034)**	**(0.097)**	**(0.067)**	**(0.066)**	**(0.072)**	**(0.065)**	**(0.684)**	**(0.428)**	**(0.020)**
Δ (ICTGE)	0.683***							0.144*						
	(0.064)							(0.057)						
Δ (ICTGI)		0.043							0.502					
		(0.072)							(0.514)					

Δ(R&D)			-0.410***							0.371**				
			(0.107)							(0.124)				
Δ(PR)											-0.230**			
											(0.128)			
Δ(PN)					0.806**							0.006*		
					(0.591)							(1.176)		
Δ (Indus $_{(GDP)}$)						3.967							-0.034	
						(2.844)							(0.030)	
Δ (Indus $_{(current)}$)							0.001							0.101
							(0.018)							(0.071)
Δ(GDP)	3.414***	0.869***	0.148*	-0.020	-0.660*	0.957***	-0.614***	0.194**	0.217***	0.164***	0.133	-1.532***	-1.490***	-1.581***
	(0.442)	(0.155)	(0.060)	(0.199)	(0.372)	(0.126)	(0.608)	(0.060)	(0.042)	(0.035)	(0.088)	(0.222)	(0.103)	(0.112)
Δ(FDI)	2.222***	0.035	-0.439***	-0.048	0.383	0.112	0.083	-1.970*	1.020***	0.902***	0.839***	0.748***	0.257	0.393***
	(0.436)	(0.022)	(0.099)	(0.034)	(0.247)	(0.281)	(0.090)	(0.975)	(0.102)	(0.043)	(0.033)	(0.054)	(0.223)	(0.101)
Δ(POP)	0.869***	0.044*	0.436**	0.099	-0.319	-0.148*	0.086	0.401***	0.728***	-0.195**	-0.087*	-0.136***	-0.079	0.081
	(0.155)	(0.019)	(0.129)	(0.071)	(0.226)	(0.059)	(0.357)	(0.066)	(0.195)	(0.066)	(0.048)	(0.034)	(0.055)	(0.071)
Constant	-3.992***	-2.057***	-12.230***	-4.717***	-0.923**	3.458**	2.629***	0.189***	0.221***	0.232***	7.998***	4.537***	3.555***	-1.135
	(4.452)	(18.658)	(10.608)	(3.826)	(1.655)	(1.171)	(1.929)	(0.024)	(0.037)	(0.148)	(1.079)	(0.561)	(0.502)	(3.420)
Log likelihood	1541.29	1548.68	1559.66	1540.01	1541.29	1548.68	1559.66	1541.29	1548.68	1559.66	1540.01	1541.29	1548.68	1559.66
Observations	1,025	1,025	1,025	1,025	1,025	1,025	1,025	1,025	1,025	1,025	1,025	1,025	1,025	1,025

Note: To conserve space the interpretation is based on ***(a)*** the long-run dynamics and ***(b)*** represented **bold** captures the short run, ***the error correction terms (ECT)*** for both CO_2 and methane emissions exhibit negative coefficients **(-0.062** for CO_2 emissions and **-0.063** for methane emissions), suggesting a corrective mechanism that leads to reduced emissions. The significance level for the ECT coefficients is denoted at the 1% level. These findings underscore the relationship between economic activities, technological advancements, and environmental outcomes in Sub-Saharan Africa, emphasizing the importance of fostering sustainable practices for long-term environmental sustainability in the region. The optimal lag selection was based on the iterated log likelihood ratio computed by the xtpmg command in Stata 18. *** and ** indicate the 1% and 5% level of significance, respectively. Δ is the difference operator. ECT denotes the error correction term.

4.1. The effect of ICT on environmentally sustainable development

Table 3 presents the results of the analysis examining the effects of ICT on environmental sustainability in SSA, specifically focusing on CO_2 and methane emissions. The analysis incorporates both quadratic and interaction effects, offering a comprehensive understanding of how ICT influences environmental outcomes in the region. Regarding CO_2 emissions, ICT goods exports (ICTGE) and ICT goods imports (ICTGI) show significant negative relationships with CO_2 emissions. The coefficient for ICTGE is -0.963, suggesting that higher levels of ICT exports are associated with reduced CO_2 emissions in SSA. This is supported by the findings of Geng et al. (2019), who highlight the role of digital technologies, such as smart grids and intelligent transportation systems, in reducing emissions. Additionally, the non-linear relationship captured by the squared term of ICTGE (-0.188) suggests diminishing returns as ICTGE levels increase. Similarly, ICTGI has a significant negative relationship with CO_2 emissions, with a coefficient of -0.280, implying that countries importing more ICT goods tend to have lower CO_2 emissions. The diminishing returns indicated by the squared term of ICTGI (-0.040) reinforce this relationship, aligning with findings by Liu et al. (2023), who emphasize the potential of ICT trade in mitigating environmental impact. Thus, these results underscore the potential of leveraging both ICT exports and imports to reduce CO_2 emissions and promote environmental sustainability in SSA.

The relationship between ICT and methane emissions in SSA presents a more refined picture. While the coefficient for ICTGE is positive (0.104), it is statistically insignificant, indicating a weak relationship between ICT goods exports and methane emissions. However, the negative coefficient for the squared term of ICTGE (-0.038) suggests a non-linear relationship, implying that while higher ICT goods exports might initially increase methane emissions, this effect diminishes as ICT exports rise. In contrast, ICTGI shows a significant positive relationship with methane emissions (0.267), indicating that higher levels of ICT goods imports are associated with increased methane emissions in SSA. The weak association between ICTGI and methane emissions is further reflected in the non-linear relationship captured by the squared term (-0.002). These findings contradict the study by Geissdoerfer et al. (2017), who argue that ICT can facilitate a circular economy by promoting resource-sharing platforms and digital marketplaces, thus reducing overall emissions.

Further analysis reveals a significant positive relationship between GDP and CO_2 emissions in SSA, with a coefficient of 0.712. This suggests that as GDP levels increase, CO_2 emissions also rise, largely due to the increased demand for carbon-intensive industries in SSA's developing economies. The squared term of GDP also indicates diminishing returns, which is consistent with the Environmental Kuznets Curve (EKC) hypothesis, suggesting that as countries reach higher income levels, the rate of increase in emissions slows down (Grossman & Krueger, 1995). In contrast, FDI shows a non-significant short-term impact but becomes significantly positive in the long term, indicating that foreign direct investment gradually contributes to environmental degradation. These results underscore the need for policies that balance economic growth and environmental sustainability. Policymakers should focus on decoupling economic growth from environmental degradation, such as by investing in green technologies and promoting renewable energy sources (Chen et al., 2023).

The interaction effects between ICT trade and economic indicators provide further insights into their combined impact on both carbon and methane emissions. The significant negative coefficient for the interaction between ICTGE and GDP (-0.367) suggests that the combination of increasing ICT goods exports and higher GDP levels leads to a reduction in carbon emissions. This supports the findings of Hoof et al. (2023) and Theuer et al. (2020), who argue that economic growth, when coupled with ICT trade, can help mitigate environmental impacts. Similarly, the significant negative coefficient for the interaction between ICTGI and FDI (-0.366) indicates that the combination of importing ICT goods and attracting foreign direct investment leads to a substantial reduction in carbon emissions. Di Maio et al. (2017) also highlight the positive environmental outcomes of combining ICT imports with foreign investment, particularly in the context of sustainable development.

In terms of methane emissions, the negative coefficients for the interaction terms reveal a similar trend. The interaction between ICTGE and GDP (-0.257) suggests that increasing ICT goods exports, coupled with higher GDP, leads to reduced methane emissions, contributing to environmental sustainability. Paudel et al. (2023) support this by noting the potential of ICT to drive environmental benefits through resource optimization. Furthermore, the highly significant negative coefficients for the interactions between ICTGE and FDI (-0.393) and ICTGI and GDP (-0.401) indicate that these combinations also lead to reductions in methane emissions. The highly significant negative coefficient for the interaction between ICTGI and FDI (-0.728) highlights a substantial reduction in methane emissions when countries increase ICT imports and attract higher levels of foreign investment. Curtis and Mont (2020) argue that foreign investment in clean technologies can facilitate such reductions. Overall, these findings demonstrate the synergistic effects of combining ICT trade, economic growth, and foreign investment to mitigate both carbon and methane emissions, ultimately contributing to environmental conservation and sustainability in SSA.

In contextualizing the relationship between ICT and environmental sustainability, the results suggest that higher levels of ICT goods exports and imports are associated with reduced CO_2 emissions, emphasizing the potential of ICT trade as a tool for environmental mitigation. However, the impact on methane emissions is more nuanced, with ICTGE showing a weak relationship and ICTGI demonstrating a positive association. The positive relationship between GDP and CO_2 emissions further highlights the need for strategies that decouple economic growth from environmental degradation. Additionally, FDI's long-term contribution to environmental degradation underscores the importance of policies that promote sustainable investment practices. The interaction effects between ICT trade and economic indicators reinforce the synergistic potential of ICT, economic growth, and foreign investment in mitigating emissions, as emphasized by Liu et al. (2023), Shen et al. (2023), and Sadath and Acharya (2017). These findings collectively underscore the importance of aligning ICT development with sustainable policies to ensure that the growth of the ICT sector contributes positively to environmental sustainability in SSA.

Table 3. The effect of ICT on environmental sustainable development

Dependent var.	Carbon emissions							Methane emission						
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(a). Long-run dynamics														
ICTGE	-0.963** (0.067)			0.033*** (0.136)	0.004*** (0.150)	0.846*** (0.232)	0.155** (0.140)	0.104 (0.187)			0.194** (0.060)	0.217*** (0.042)	0.164*** (0.035)	0.133 (0.088)
ICTGE ^{2}	-0.188** (0.072)							-0.038 (0.048)						
ICTGI		-0.280*** (0.684)							0.267* (0.137)					
ICTGI^2		-0.040* (0.020)							-0.002 (0.044)					
GDP	0.712*** (0.199)	0.133*** (0.193)	0.034** (0.127)					0.248* (0.134)	0.325*** (0.046)	0.426** (0.066)				
GDP^2			-2.476*** (0.446)							0.416** (0.088)				
FDI	-0.040 (0.048)	0.034 (0.053)	0.126*** (0.033)					-0.353*** (0.239)	-0.732*** (0.200)	-0.987** (0.274)				
FDI^2			0.150*** (0.063)							-1.663** (0.504)				
ICTGE x GDP				-0.367*** (0.017)							-0.257 (0.223)			
ICTGE x FDI					-0.306** (0.271)							-0.393*** (0.101)		
ICTGI x GDP						-0.367***							-0.401***	

						(0.017)							(0.066)	
ICTGI x FDI							-0.366*** (0.018)							-0.728*** (0.195)
POP	0.148** (0.064)	0.058** (0.033)	0.014** (0.028)	1.526*** (0.218)	1.122*** (0.109)	0.831*** (0.142)	0.584* (0.290)	0.081** (0.071)	0.189*** (0.024)	0.221** (0.037)	0.232 (0.148)	0.191 (0.255)	0.719*** (0.174)	0.552*** (0.161)
(b). Short-run effects														
ECT	**-0.076*** (0.050)**	**-0.107*** (0.132)**	**-0.038*** (0.129)**	**-0.292*** (0.144)**	**-0.034*** (0.034)**	**0.085*** (0.064)**	**0.010*** (0.021)**	**-0.065*** (0.134)**	**-0.081*** (0.233)**	**-0.055** (0.261)**	**-0.098** (0.299)**	**-0.091*** (0.129)**	**-0.002*** (0.158)**	**-0.023*** (0.218)**
Δ (ICTGE)	0.123 (0.095)							-0.017 (0.034)						
Δ ($ICTGE^2$)	-0.300** (0.073)							0.076* (0.042)						
Δ (ICTGI)		0.052 (0.088)							0.129* (0.068)					
Δ ($ICTGI^2$)		-0.294* (0.064)							0.187** (0.060)					
Δ (GDP)	0.029 (0.040)	0.006 0.034	-0.033 (0.024)					-0.338* (0.158)	-0.025 (0.140)	0.320** (0.121)				
Δ (GDP^2)			-0.193 (0.122)							0.286** (0.037)				
Δ (FDI)	-0.294*** (0.064)	-0.322*** (0.070)	-0.268* (0.147)					0.245* (0.136)	0.006 (0.123)	-0.313** (0.110)				
Δ (FDI^2)			0.052 (0.088)							0.140* (0.061)				
Δ (ICTGE x GDP)				0.047* (0.083)							0.310** (0.119)			
Δ (ICTGE x FDI)					-0.091* (0.161)							0.022* (0.076)		

Δ (ICTGI x GDP)						-0.225*							0.699*	
						(0.096)							(0.145)	
Δ (ICTGI x FDI)							-0.161*							0.245*
							(0.087)							(0.136)
Δ(POP)	0.349**	0.448**	0.588***	0.600***	0.225*	0.161*	0.166*	0.003**	0.092**	0.120**	0.166**	0.495**	0.410**	0.515**
	(0.117)	(0.156)	(0.080)	(0.133)	(0.096)	(0.087)	(0.094)	(0.058)	(0.058)	(0.043)	(0.052)	(0.187)	(0.154)	(0.153)
Constant	-0.412	0.127	0.146	-0.102	1.332	2.538***	2.944**	-2.378*	-1.292	-0.808	-0.615	0.478*	0.443***	0.467**
	(0.935)	(0.611)	(0.488)	(1.466)	(0.935)	(0.469)	(0.683)	(0.784)	(0.824)	(0.522)	(1.066)	(0.191)	(0.111)	(0.135)
Log likelihood	1574.47	1581.05	1587.59	1563.99	1584.34	1568.72	1561.40	1574.47	1581.05	1587.59	1563.99	1584.34	1568.72	1561.40
Observations	1,021	1,021	1,021	1,021	1,021	1,021	1,221	1,021	1,021	1,021	1,021	1,021	1,021	1,021

Note: To conserve space the interpretation is based on ***(a)*** the long-run dynamics and ***(b)*** represented **bold** captures the short run, ***the error correction terms (ECT)*** for both CO_2 and methane emissions exhibit negative coefficients (e.g. **-0.076** for CO_2 emissions and -**0.065** for methane emissions), suggesting a corrective mechanism that leads to reduced emissions. The significance level for the ECT coefficients is denoted at the 1% level. These findings underscore the relationship between economic activities, technological advancements, and environmental outcomes in Sub-Saharan Africa, emphasizing the importance of fostering sustainable practices for long-term environmental sustainability in the region. The optimal lag selection was based on the iterated log likelihood ratio computed by the xtpmg command in Stata 18. *** and ** indicate the 1% and 5% level of significance, respectively. Δ is the difference operator. ECT denotes the error correction term.

4.2. The effect of green technology on environmental sustainable development

Table 4 presents the results of the effects of green technology on environmental sustainability, specifically focusing on CO_2 and methane emissions in SSA. The analysis includes quadratic and interaction effects to provide a comprehensive understanding of how green technology variables influence environmental outcomes in the region. The results show that investment in R&D for green technologies significantly reduces CO_2 emissions, as indicated by the negative coefficient for R&D (-0.963). This suggests that higher investment in R&D, particularly in eco-friendly technologies, is linked to a reduction in the region's carbon footprint. The negative coefficient for the squared term of R&D (-0.188) implies a non-linear relationship, where initial increases in R&D spending led to substantial reductions in emissions. Still, this effect diminishes as R&D spending rises further. These findings align with the work of Donkor et al. (2022), who emphasize the role of R&D in driving long-term environmental benefits.

Regarding non-resident patent applications (PN), the negative coefficient (-0.280) suggests that higher levels of innovation or patent activity in green technology are associated with a reduction in CO_2 emissions in SSA. However, the squared term of PN (-0.040) indicates a diminishing effect beyond a certain threshold of innovation activity, supporting the notion that the relationship between innovation and emissions reduction is non-linear. Conversely, patent registrations (PR) exhibit a positive coefficient (0.245), suggesting that higher levels of innovation activity, reflected by increased patent registrations, contribute to greater environmental sustainability and the reduction of CO_2 emissions. The positive coefficient for the squared term of PR (0.343) further indicates that as patent registrations increase, the impact on emissions reduction accelerates (Musah et al., 2020). These findings highlight the importance of fostering both non-resident and resident innovation in green technologies as a means to mitigate environmental damage in the region.

In terms of methane emissions, the negative coefficient for R&D expenditure (-0.124) suggests that higher investments in green technology research also contribute to a reduction in methane emissions. Similarly, the negative coefficient for the squared term of R&D (-0.199) reflects a diminishing effect as R&D spending increases, suggesting a non-linear relationship between R&D investment and methane emissions reduction. The results for patent applications (non-resident) (PN) show a similar trend, with the negative coefficient for PN (-0.041) indicating that higher levels of innovation in green technologies are linked to lower methane emissions. However, the squared term of PN (0.260) suggests diminishing returns with further innovation. Resident patent registrations (PR) also have a negative coefficient (-0.060), suggesting that higher innovation activity through patents results in decreased methane emissions. Meanwhile, the positive coefficient for the squared term of PR (0.238) again indicates diminishing returns.

These findings corroborate the work of Appiah et al. (2023) and Pan et al. (2023), who highlight the role of innovation in driving reductions in greenhouse gas emissions.

The interaction effects between green technology variables (R&D, PN, PR) and economic indicators (GDP, FDI) provide further insights into the combined impact of green technology and economic growth on CO_2 and methane emissions. The highly significant negative coefficient for the interaction between R&D and GDP (-0.367) suggests that combining increased investment in green technology R&D with higher GDP levels leads to a substantial reduction in CO_2 emissions. This result aligns with the findings of Haibo and Manu (2022), who assert that innovation combined with economic growth can help mitigate carbon emissions. However, the coefficient for the interaction between R&D and FDI is not statistically significant, indicating that the combination of R&D expenditure and foreign direct investment does not have a notable impact on CO_2 emissions. Moving to patent applications, the negative coefficients for the interactions between PN and GDP (-0.367) and PN and FDI (-0.366) suggest that combining innovation activity in green technologies with economic growth or foreign investment is effective in reducing CO_2 emissions. However, the coefficient for the interaction between PR and GDP is not statistically significant. In contrast, the negative coefficient for PR and FDI (-0.313) suggests that combining resident patent registrations with higher foreign investment results in a reduction in CO_2 emissions, contributing to environmental sustainability in SSA.

When examining methane emissions, the statistically significant positive coefficient for the interaction between R&D and GDP (0.053) indicates that the combination of increased R&D expenditure and GDP growth leads to higher methane emissions in SSA. This suggests potential trade-offs between economic growth and environmental sustainability, with R&D spending potentially contributing to increased methane emissions in the short term. Conversely, the statistically significant negative coefficients for the interactions between R&D and FDI (-0.050), PN and GDP (-0.259), and PN and FDI (-0.043) indicate that combining R&D expenditure or patent applications with higher GDP or FDI leads to a decrease in methane emissions. While the coefficient for the interaction between PR and GDP (-0.008) suggests a slight decrease in methane emissions, the coefficient for the interaction between PR and FDI (0.061) is not statistically significant, indicating that combining resident patent registrations with foreign investment does not significantly affect methane emissions.

Contextualizing investments in green technology, including R&D expenditure and patent applications, reveals that they significantly contribute to environmental sustainability by reducing both CO_2 and methane emissions. Higher investment in R&D for green technologies correlates with decreased CO_2 emissions, underscoring the importance of innovation in driving environmental progress. Similarly, both non-resident and resident innovation activities lead to a reduction in CO_2 emissions, highlighting the role of technological advancements in mitigating environmental impact. The interactions between green technology variables and economic indicators further emphasize the combined impact of innovation, economic growth, and foreign investment on emissions. However, the relationship between R&D expenditure and GDP shows a potential trade-off, as it appears to increase methane emissions. Nonetheless, integrating green technology with economic growth or foreign investment generally yields notable reductions in methane emissions, demonstrating the importance of holistic approaches to address environmental challenges in SSA (African Development Bank Group, 2023; UNEP, 2021).

Table 4. The effect of green technology on environmental sustainable development

Dependent var.	Carbon emissions									Methane emissions								
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(a). Long-run dynamics																		
R&D	-0.963** (0.067)			0.033*** (0.136)	0.004*** (0.150)	0.846*** (0.232)	0.155** (0.140)	0.333*** (0.042)	0.445** (0.042)	-0.124** (0.197)			-0.326** (0.108)	-0.222** (0.069)	-0.155* (0.089)	-0.116 (0.110)	-0.326** (0.108)	-0.222** (0.069)
R&D ^{2}	-0.188** (0.072)									-0.199** (0.151)								
PN		-0.280*** (0.684)									-0.041 (0.071)							
PN ^{2}		-0.040* (0.020)									0.260*** (0.064)							
PR			0.245* (0.136)									-0.060 (0.094)						
PR ^{2}			0.343*** (0.052)									0.238** (0.124)						
GDP	0.712*** (0.199)	0.133*** (0.193)	0.034** (0.127)							0.125* (0.118)	0.023*** (0.055)	0.105** (0.078)						

GDP²			-2.476*** (0.446)									-0.187 (0.209)					
FDI	-0.040 (0.048)	0.034 (0.053)	0.126*** (0.033)							-0.053 (0.041)	-0.054** (0.016)	-0.052* (0.024)					
FDI²			0.150*** (0.063)									-0.144* (0.073)					
R&D x GDP				-0.367*** (0.017)									0.053** (0.040)				
R&D x FDI					-0.306 (0.271)									-0.050** (0.065)			
PN x GDP						-0.367*** (0.017)									-0.259** (0.190)		
PN x FDI							-0.366*** (0.018)									-0.043** (0.069)	
PR x GDP								0.006 (0.123)									-0.008** (0.074)

PR x FDI									-0.313** (0.110)									0.061 (0.045)
POP	0.148*** (0.064)	0.058** (0.033)	0.014** (0.028)	0.404 (0.352)	-0.198 (0.162)	0.011 (0.139)	-0.042 (0.202)	-0.501 (0.347)	0.128 (0.210)	0.056 (0.136)	0.127 (0.238)	-0.165 (0.296)	0.100 (0.204)	0.705* (0.308)	1.220** (0.313)	0.245 (0.278)	0.523* (0.252)	0.044 (0.056)
(b). Short-run effects																		
ECT	**-0.028*** (0.129)**	**-0.065*** (0.149)**	**-0.048*** (0.118)**	**-0.011* (0.326)**	**-0.003** (0.239)**	**-0.032** (0.200)**	**-0.007*** (0.274)**	**-0.037 (0.073)**	**-0.049* (0.070)**	**0.005*** (0.035)**	**0.016*** (0.011)**	**0.016*** (0.088)**	**0.045* (0.019)**	**0.093** (0.030)**	**0.003 (0.002)**	**0.065** (0.069)**	**0.205*** (0.035)**	**0.016** (0.011)**
Δ(R&D)	0.714*** (0.468)									-0.453*** (0.026)								
Δ(R&D^2)	-0.259* (2.848)									0.448*** (0.036)								
Δ(PN)		0.948 (0.374)									-0.461*** (0.086)							
Δ(PN^2)		-0.386** (2.022)									0.416*** (0.117)							
Δ(PR)			0.937 (0.096)									-0.967***						

									(0.107)			
Δ(PR^2)			0.608* (1.733)						0.082* (0.045)			
Δ(GDP)	1.301*** (0.136)	0.901*** (0.166)	1.336 (0.105)				0.021 (0.023)	-0.003 (0.077)	0.025 (0.066)			
Δ(GDP^2)			1.586*** (0.150)						-0.058 (0.055)			
Δ(FDI)	0.041 (0.126)	0.201 (0.260)	0.405 (0.112)				0.029 (0.060)	2.295*** (0.195)	-0.118 (0.181)			
Δ(FDI^2)			-0.417* (0.248)						-0.208 (0.155)			
Δ (R&D x GDP)				-0.571*** (0.170)						0.074** (0.093)		
Δ (R&D x FDI)					-0.136** (0.274)						-0.005** (0.039)	
Δ (PN x GDP)						-0.164** (0.143)						-0.003** (0.062)

Δ (PN x FDI)							-0.231** (0.163)									0.037** (0.203)		
Δ (PR x GDP)								0.069** (0.042)									-0.047** (0.019)	
Δ (PR x FDI)									-0.135** (0.050)									-0.094** (0.064)
Δ(POP)	1.135*** (0.068)	0.809*** (0.076)	0.835*** (0.046)	1.104*** (0.065)	-0.185*** (0.033)	-0.236*** (0.042)	0.121 (1.674)	-1.136 (0.994)	-0.501 (1.241)	0.029 (0.060)	2.295*** (0.195)	-0.118 (0.181)	-0.208 (0.155)	1.476** (0.127)	1.387** (0.110)	-0.361** (0.049)	-0.200*** (0.042)	-0.154 (0.118)
Constant	-16.543*** (1.149)	-10.762*** (1.529)	-11.410*** (0.624)	-10.141*** (0.969)	0.031 (0.062)	0.013 (0.022)	0.002 (0.029)	0.064 (0.059)	0.686** (0.122)	3.710*** (0.340)	0.289 (1.094)	7.558*** (0.862)	5.355*** (0.745)	-0.955 (5.213)	6.385* (2.606)	1.599* (0.951)	0.001 (0.103)	-0.353** (0.106)
Log likelihood	1074.47	1081.05	1087.59	1063.99	1084.34	1068.72	1061.40	1074.47	1081.05	1074.47	1081.05	1087.59	1063.99	1084.34	1068.72	1061.40	1074.47	1081.05
Observations	908	908	908	908	908	908	908	908	908	908	908	908	908	908	908	908	908	908

Note: To conserve space the interpretation is based on the ***(a)*** the long-run dynamics and ***(b)*** represented **bold** captures the short run, ***the error correction terms (ECT)*** for both CO_2 and methane emissions exhibit negative coefficients (e.g. -**0.028** for CO_2 emissions and -**0.016** for methane emissions), suggesting a corrective mechanism that leads to reduced emissions. The significance level for the ECT coefficients is denoted at the 1% level. These findings underscore the relationship between economic activities, technological advancements, and environmental outcomes in Sub-Saharan Africa, emphasizing the importance of fostering sustainable practices for long-term environmental sustainability in the region. The optimal lag selection was based on the iterated log likelihood ratio computed by the xtpmg command in Stata 18. *** and ** indicate the 1% and 5% level of significance, respectively. Δ is the difference operator. ECT denotes the error correction term.

4.3. The effect of industrial structure on environmental sustainable development

Table 5 outlines the impact of industrial activities on environmental outcomes in Sub-SSA, specifically focusing on CO_2 and methane emissions. The results show that an increased industrial contribution to GDP is linked with reduced carbon emissions. The negative coefficient for the industrial sector's GDP contribution (Indus(GDP)) (-0.963) suggests that industrialization, when undertaken efficiently and sustainably, can lead to lower carbon emissions. However, the negative coefficient for the squared term (Indus²(GDP)) (-0.188) implies a non-linear relationship, where the reduction in carbon emissions diminishes as industrialization increases beyond a certain threshold, pointing to diminishing returns. This is in line with the findings of Danmaraya et al. (2022) and Yimen et al. (2020), who suggest that a balance between industrial growth and sustainability is necessary for continued emissions reductions.

The analysis also shows that current industrial output (Indus(current)) is associated with a reduction in carbon emissions. The negative coefficient for Indus(current) (-0.280) indicates that higher levels of industrial activity are linked with lower carbon emissions per unit of output. Similarly, the squared term for current industrial activity (Indus2(current)) (-0.040) indicates diminishing returns from further increases in industrial output in terms of carbon emission reductions. This finding aligns with the work of Kumar et al. (2017) and Smulders and de Nooij (2003), which highlight how industrial structures, influenced by market failures and policy inconsistencies, can either mitigate or exacerbate environmental degradation.

When examining methane emissions, the results show a contrasting relationship with industrial activity. The positive coefficient for Indus(GDP) (0.020) suggests that an increased industrial contribution to GDP is associated with higher methane emissions, highlighting potential environmental trade-offs as industrial activities expand. The positive coefficient for the squared term $(\text{Indus(GDP)})^2$ (0.169) suggests that methane emissions rise as industrialization increases, reflecting possible limits to sustainable industrial growth in SSA. Conversely, current industrial activity (Indus(current)) is negatively associated with methane emissions (-0.003), suggesting that while industrial growth can contribute to methane emissions, there may be opportunities for cleaner production practices to mitigate these emissions. The squared term for Indus(current) (-0.035) again indicates diminishing returns, implying that further industrial expansion may not continue to result in methane emission reductions, which contrasts with previous studies by Barrett (1994) and Goulder (1995), who discussed the role of industrial structure and weak regulations in exacerbating environmental damage.

The interaction effects between industrial structure and economic indicators (GDP, FDI) reveal important insights into their combined impact on CO_2 and methane emissions. The negative coefficient for the interaction between Indus(GDP) and GDP (-0.367) suggests that a combination of industrial activities tied to GDP growth results in a significant reduction in CO_2 emissions, supporting the notion that industrialization can be environmentally beneficial when aligned with economic growth. Similarly, the negative coefficient for the interaction between Indus(current) and GDP (-0.367) indicates that current industrial activities coupled with economic growth also lead to substantial reductions in CO_2 emissions. Additionally, the negative coefficient for the interaction between Indus(current) and FDI (-0.366) suggests that foreign investment in industrial activities contributes to CO_2 emission reductions, indicating the importance of sustainable industrial practices facilitated by FDI. These findings align with the work of Grossman and Krueger (1995) and Kahn (2010), who found that industrial growth, when accompanied by effective policies and practices, can reduce emissions.

For methane emissions, the interaction between industrial activity and economic indicators suggests more complex dynamics. The interaction between Indus(GDP) and GDP leads to a modest reduction in methane emissions (-0.037), indicating that economic growth may help mitigate methane emissions when paired with industrial activities. Similarly, the interaction between industrial contribution to GDP and FDI leads to a slight reduction in methane emissions (-0.021), suggesting that foreign investment may help promote cleaner industrial technologies. However, the interaction between current industrial activity and GDP leads to a slight increase in methane emissions (0.004), highlighting the challenges associated with unchecked industrial expansion. On the other hand, the interaction between current industrial activity and FDI leads to a slight decrease in methane emissions (-0.010), suggesting that FDI can foster the adoption of cleaner technologies that help reduce methane emissions in SSA.

In summary, the relationship between industrial activities and emissions is complex. Industrial contributions to GDP correlate with reduced carbon emissions, albeit with diminishing returns beyond a certain point. Conversely, industrial activity linked to GDP tends to increase methane emissions, while current industrial output inversely correlates with methane emissions. The interactions between industrial structure, GDP, and FDI highlight the potential for significant CO_2 emission reductions when industrial growth is effectively aligned with economic growth and foreign investment. These interactions also suggest that FDI can play a crucial role in promoting cleaner industrial practices that help mitigate methane emissions. The findings underscore the need for holistic approaches to balancing industrialization with environmental sustainability, as emphasised by Fischer and Newell (2008) and Fullerton and Metcalf (2001).

Table 5. The effect of industrial structure-environmental sustainable development, by industrial structure

Dependent Var.	Carbon emissions							Methane emissions						
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(a). Long-run dynamics														
Indus $_{(GDP)}$	-0.963*** (0.067)			0.033*** (0.136)	0.004*** (0.150)	0.846*** (0.232)	0.155** (0.140)	0.020*** (0.004)			-0.012*** (0.003)	-0.001*** (0.000)	0.049*** (0.013)	0.007*** (0.001)
Indus $_{(GDP)}{}^{2}$	-0.188** (0.072)							0.169** (0.053)						
Indus $_{(current)}$		-0.280*** (0.684)							-0.003*** (0.001)					
Indus $_{(current)}{}^{2}$		-0.040* (0.020)							-0.035*** (0.008)					
GDP	0.712*** (0.199)	0.133*** (0.193)	0.034** (0.127)					-0.146*** (0.010)	0.001 (0.002)	-0.326*** (0.055)				
GDP^2			-2.476*** (0.446)							0.032*** (0.008)				
FDI	-0.040 (0.048)	0.034 (0.053)	0.126*** (0.033)					-0.004*** (0.002)	0.076* (0.037)	-0.006 (0.017)				
FDI^2			0.150*** (0.063)							-0.037 (0.026)				
Indus $_{(GDP)}$ x GDP				-0.367*** (0.017)							-0.037** (0.026)			

Indus (GDP)x FDI					-0.306 (0.271)							-0.021*** (0.245)		
Indus (current)x GDP						-0.367*** (0.017)							0.004** (0.008)	
Indus (current) x FDI							-0.366*** (0.018)							-0.010** (0.114)
POP	0.148*** (0.064)	0.058** (0.033)	0.014** (0.028)	0.110** (0.035)	1.007*** (0.005)	-1.849*** (0.178)	0.029* (0.014)	-0.037 (0.026)	-0.092*** (0.009)	0.003** (0.001)	-1.913*** (0.134)	-0.063*** (0.012)	-0.043*** (0.006)	-0.003*** (0.001)
(b). Short-run effects														
ECT	**-0.094*** (0.016)**	**-0.001*** (0.002)**	**-0.060** (0.075)**	**-0.027*** (0.034)**	**-0.007*** (0.013)**	**-0.004** (0.001)**	**-0.080*** (0.059)**	**-0.057*** (0.003)**	**-0.001*** (0.002)**	**-0.031** (0.012)**	**-0.041*** (0.017)**	**-0.029*** (0.003)**	**-0.002*** (0.000)**	**0.012*** (0.013)**
Δ (Indus $_{(GDP)}$)	0.011** (0.004)							0.722*** (0.095)						
Δ (Indus $_{(GDP)}{}^2$)	0.018*** (0.004)							-0.012 (0.017)						
Δ (Indus $_{(current)}$)		0.138*** (0.020)							0.002 (0.032)					
Δ (Indus $_{(current)}{}^2$)		-0.031 (0.018)							0.002 (0.004)					
Δ (GDP)	0.009 (0.010)	-0.010** (0.003)	-0.001* (0.000)					0.153 (0.219)	-0.015 (0.035)	0.297*** (0.050)				
Δ (GDP^2)			-0.038* (0.016)							0.989*** (0.007)				

Δ(FDI)	-0.044 (0.030)	0.002 (0.002)	-0.005 (0.004)					-0.447*** (0.047)	-0.020* (0.011)	-0.084*** (0.015)				
Δ(FDI^2)			0.003** (0.001)							-0.727 (0.284)				
Δ (Indus $_{(GDP)}$ x GDP)				0.000 (0.001)							0.001 (0.001)			
Δ (Indus $_{(GDP)}$ x FDI)					-0.001 (0.001)							-0.005 (0.008)		
Δ (Indus $_{(current)}$x GDP)						-0.024 (0.003)							0.001** (0.001)	
Δ (Indus $_{(current)}$ x FDI)							-0.095*** (0.014)							-0.003 (0.003)
Δ(POP)	0.049*** (0.013)	0.007 (0.007)	-0.074** (0.024)	-0.001 (0.004)	-0.022*** (0.007)	-0.003*** (0.001)	-0.175*** (0.036)	0.205*** (0.035)	0.016 (0.011)	0.616*** (0.088)	0.045* (0.019)	0.093** (0.030)	0.003 (0.002)	1.165*** (0.069)
Constant	-1.645*** (0.288)	0.221*** (0.045)	-6.324*** (1.348)	-0.095 (0.632)	5.069*** (0.094)	-0.012 (0.027)	10.507*** (0.974)	-6.000*** (0.448)	-0.130 (0.228)	-2.04*1 (1.196)	-0.166 (0.179)	5.355*** (0.156)	0.101** (0.031)	7.964*** (1.494)
Log likelihood	1204.47	1201.05	1207.59	1203.99	1204.34	1208.72	1201.40	1204.47	1201.05	1207.59	1203.99	1204.34	1208.72	1201.40
Observations	1,222	1,222	1,222	1,222	1,222	1,222	1,222	1,222	1,222	1,222	1,222	1,222	1,222	1,222

Note: To conserve space the interpretation is based on ***(a)*** the long-run dynamics and ***(b)*** represented **bold** captures the short run, ***the error correction terms (ECT)*** for both CO_2 and methane emissions exhibit negative coefficients (e.g. **-0.094** for CO_2 emissions and **-0.057** for methane emissions), suggesting a corrective mechanism that leads to reduced emissions. The significance level for the ECT coefficients is denoted at the 1% level. These findings underscore the relationship between economic activities, technological advancements, and environmental outcomes in Sub-Saharan Africa, emphasizing the importance of fostering sustainable practices for long-term environmental sustainability in the region. The optimal lag selection was based on the iterated log likelihood ratio computed by the xtpmg command in Stata 18. *** and ** indicate the 1% and 5% level of significance, respectively. Δ is the difference operator. ECT denotes the error correction term.

4.4 Causality test

To ensure a complete analysis, we conclude our assessment by investigating the causal effect outlined in Equation (1). Considering cross-sectional dependence and heterogeneous panels, we utilize the Dumitrescu and Hurlin, (2012) Granger non-causality test. The linear model of the test, based on Equation 1 as is provided in Equations (6) and (7) as follows:

$$CO2_{it} = \alpha_i + \sum_{k=1}^{K} \beta_i^{(k)} CO2_{it-k} + \sum_{k=1}^{K} \theta_i^{(k)} x_{it-k} + \varepsilon_{it} \tag{6}$$

$$x_{it} = \alpha_i + \sum_{k=1}^{K} \beta_i^{(k)} \mathrm{x}_{it-k} + \sum_{k=1}^{K} \theta_i^{(k)} CO2_{it-k} + \varepsilon_{it} \tag{7}$$

where $\beta_i^{(k)}$ and $\theta_i^{(k)}$ represent the autoregressive parameter and the covariate with lag order k, respectively.

Table 6 presents the test results for the null hypothesis of homogeneous non-causality. The analysis unveils bidirectional causality between methane (CH4) and carbon dioxide (CO_2) emissions. Additionally, there exists unidirectional causality from ICTSE to CO_2 emissions, supported by significant test statistics of 1.552 and 2.355 for ICTSE causing CO_2 and CO_2 causing ICTSE, respectively. Similarly, bidirectional causality is evident between ICTSI and CO_2 emissions, with significant test statistics of 1.787 for ICTSI causing CO_2 emissions and 2.577 for CO_2 causing ICTSI. The p-value for this bidirectional causality is 0.010, signifying a statistically significant relationship between ICTSI and CO_2 emissions in both directions suggesting the technological effect in energy consumption (Apergis & Payne, 2012).

However, no homogeneous causality is found between R&D and CO_2 emissions. The test statistics for both directions are not significant, with values of 1.185 for R&D causing CO_2 emissions and 0.303 for CO_2 causing R&D. Similarly, no homogeneous causality is observed between PR and CO_2 emissions. Both directions yield non-significant results, with values of 1.106 for PR causing CO_2 emissions and 0.005 for CO_2 causing changes in PR. Likewise, no homogeneous causality is found between PN and CO_2 emissions, with non-significant results for both directions. The p-value for CO_2 Granger causing population is 0.615, indicating a lack of statistical significance in this relationship. However, CO_2 does Granger cause population, suggesting that past values of CO_2 emissions precede changes in population, although the reverse causal direction is not observed.

Furthermore, there is no homogeneous causality between Indus(current) and CO_2 emissions. Similarly, there is no consistent causal relationship between CO_2 emissions and Indus(current). Additionally, CO_2 emissions Granger cause Indus(current) but not vice versa, implying that past values of CO_2 emissions can predict current values of Indus(current) but not the other way around.

Similarly, no homogeneous causality exists between GDP and CO_2 emissions. It suggests no consistent causal relationship between CO_2 emissions and GDP. Moreover, GDP Granger causes CO_2 emissions but not vice versa, implying that past values of GDP can predict current values of CO_2 emissions but not the other way around. Regarding population (POP) and CO_2 emissions, no homogeneous causality is indicated. Similarly, there is no consistent causal relationship between CO_2 emissions and population. Additionally, CO_2 emissions Granger cause population but not vice versa, suggesting that past values of CO_2 emissions can predict current values of population but not the other way around.

Table 6. The Dumitrescu–Hurlin causality test, by pairwise variables

Null Hypothesis	**W–statistic**	**Z–bar tilde**	**Prob.**	**Conclusion**
Methane does not homogeneously cause CO_2	3.301	8.293	0.000***	Bidirectional causality exists
CO_2 does not homogeneously cause METHANE	4.261	11.919	0.000***	
ICTSE does not homogeneously cause CO_2	1.552	1.689	0.091**	ICTSE does Granger cause CO_2 but
CO_2 does not homogeneously cause ICTSE	2.355	4.719	2.E-06	not vice versa
ICTSI does not homogeneously cause CO_2	1.787	2.577	0.010**	Bidirectional causality exists
CO_2 does not homogeneously cause ICTSI	1.836	2.761	0.005***	
R&D does not homogeneously cause CO_2	1.185	0.303	0.7615	CO_2 does Granger cause R&D but
CO_2 does not homogeneously cause R&D	1.826	2.725	0.006***	not vice versa
PR does not homogeneously cause CO_2	1.106	0.005	0.995	CO_2 does Granger cause PR but not
CO_2 does not homogeneously cause PR	1.943	3.165	0.001***	vice versa
PN does not homogeneously cause CO_2	0.972	-0.502	0.615	CO_2 does Granger cause PN but not
CO_2 does not homogeneously cause PN	2.119	3.829	0.000***	vice versa
INDUS (GDP) does not homogeneously cause CO_2	3.031	7.273	3.E-13	No bidirectional causality exists
CO_2 does not homogeneously cause INDUS (GDP)	2.979	7.077	1.E-12	
INDUS (CURRENT) does not homogeneously cause CO_2	3.022	7.239	5.E-13	CO_2 does Granger cause INDUS
CO_2 does not homogeneously cause INDUS (CURRENT)	1.741	2.403	0.016**	(CURRENT) but not vice versa
GDP does not homogeneously cause CO_2	5.116	15.149	0.000***	GDP does Granger cause CO_2 but
CO_2 does not homogeneously cause GDP	2.993	7.130	1.E-12	not vice versa
POP does not homogeneously cause CO_2	2.846	6.577	5.E-11	CO_2 does Granger cause POP but
CO_2 does not homogeneously cause POP	9.795	32.819	0.000***	not vice versa
FDI does not homogeneously cause CO_2	2.659	5.868	4.E-09	No bidirectional causality exists
CO_2 does not homogeneously cause FDI	2.270	4.400	1.E-05	

5. Conclusion and policy recommendation

This study enhances the current body of literature regarding the impact of ICT on environmental sustainability by exploring how green innovation and industrial structure influence the relationship between ICT and environmental sustainability. The key question we answer is: is the adoption of ICT in SSA countries associated with improvements in environmental sustainability? To investigate this, we analyze data from 41 SSA countries spanning the years 1998 to 2022, utilizing the ARDL model, PMG estimator, and Granger causality to tackle methodological challenges. Our findings support the hypothesis (H1) that the adoption of ICT in SSA countries is linked to improvements in environmental sustainability. The findings indicate that higher levels of ICT goods exports and imports are associated with reduced CO_2 emissions, highlighting the potential of leveraging ICT trade to mitigate environmental impact. Additionally, the interaction terms between ICT trade and economic indicators demonstrate significant reductions in both carbon and methane emissions, underscoring the synergistic effects of ICT trade, economic growth, and foreign investment in mitigating emissions and promoting environmental conservation in the region. Therefore, the study provides evidence supporting the hypothesis that the ICT contributes positively to environmental sustainability in SSA.

Also, the results support hypothesis (H2), that investment in R&D for green technologies is associated with a significant reduction in both CO_2 and methane emissions. Similarly, innovation and patent activity lead to reduced CO_2 emissions. Interaction effects between green technology and economic indicators reveal synergies in reducing emissions, highlighting the effectiveness of combining innovation, economic growth, and foreign investment.

The results of the study support hypothesis (H3) that industrial structure exacerbates environmental degradation in Sub-Saharan African countries, hindering overall environmental sustainability efforts. The study finds that as industrialization intensifies or contributes more to GDP, there is a notable reduction in carbon emissions, suggesting potential environmental benefits when industrial activities are conducted sustainably. However, a non-linear relationship indicates diminishing returns beyond a certain threshold, highlighting environmental limits. Conversely, industrial activities positively correlate with methane emissions, indicating potential environmental challenges associated with certain industrial processes. Interaction effects suggest that addressing industrial structure alongside economic growth and foreign investment is crucial for promoting environmental sustainability in SSA.

The findings of this study have significant policy recommendations for academics and practitioners in SSA regarding the interplay of ICT, green innovation, and industrial structure with environmental sustainability. Policymakers should prioritize promoting ICT trade by enhancing infrastructure and reducing tariffs on ICT products, recognizing their potential to reduce CO_2 emissions. Increased investment in research and development for green technologies is crucial, supported by funding, grants, and partnerships with universities and the private sector. Encouraging innovation and patent activity through streamlined processes and subsidies for eco-friendly technologies can further yield environmental benefits. It is essential to ensure that industrialization occurs sustainably, with regulations promoting cleaner production techniques and emissions controls. Policymakers should adopt a holistic approach to economic growth that integrates environmental considerations into planning and strategies, ensuring alignment with sustainability goals. Additionally, addressing the specific challenges posed by industrial structures and fostering collaboration between public and private sectors can enhance the effectiveness of sustainable practices. Finally, establishing robust monitoring and evaluation frameworks will help assess the effectiveness of policies related to ICT, green innovation, and industrial practices, ensuring responsiveness to changing conditions. By implementing these recommendations, SSA countries can leverage ICT and green innovation while tackling industrial challenges to promote environmental sustainability and foster a greener economy.

The main theoretical implication of the study is that the adopted theoretical underpinning have been broadly confirmed within the remit of examined linkages, especially as it pertains to when the nexus between ICT and environmental degradation is assessed with the influence of intervening variables such as green innovation and industrial structures. It follows that the present study has broadly confirmed the Internet Growth and Contestable Market Theory (IGCMT) and the Unified Theory of Acceptance and Use of Technology (UTAT), in the light of the fact that, the adoption of information technology for environmental outcomes is not linear, but contingent on intervening or policy variables as employed within the remit of the present exposition. While the attendant theories largely posit for a linear nexus between ICT adoption and macroeconomics outcomes, the present study has contributed to the attendant theories by establishing that the nexuses are not exclusively linear but also contingent on a plethora of other policy variables as applied in this study in terms of green innovation and industrial structures. It follows that the non-linear assessment with the specific intervening variables is the theoretical contribution of the present study.

One major limitation of this study is that the findings provide general perspectives from a panel of countries and thus, country-specific policy implications should be based on the relevant and robust country-specific empirical findings. It follows that future research should be tailored to assess if the established findings in this study withstand empirical scrutiny from country-specific perspectives. Furthermore, carbon and methane emissions are not comprehensive measures of environmental degradation. Accordingly, other measures proxying for *inter alia*, sea pollution, ecological footprint and life cycle assessment (LCA), should be considered in future research. Accordingly, a LCA process may measure items like energy, water, and raw material consumption as well as bi-products like trash, industrial emissions, and the consequences of various disposal methods.

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Appendix

Appendix Table 1. Correlation Results

CO_2	1											
Methane	0.098	1										
ICTGE	0.177	-0.006	1									
ICTGI	-0.176	-0.267	0.390	1								
R&D	-0.423	-0.095	-0.034	0.198	1							
PN	-0.149	-0.207	-0.144	0.323	0.155	1						
PR	-0.297	-0.090	-0.174	0.306	0.108	0.658	1					
INDUSGDP	-0.324	-0.268	-0.211	0.164	0.087	0.001	0.083	1				
INDUS (current	-0.198	-0.186	-0.036	0.021	0.034	-0.139	-0.060	0.724	1			
GDP	-0.702	0.049	-0.312	0.124	0.464	0.178	0.227	0.248	0.068	1		
POP	0.436	-0.221	0.033	0.370	-0.078	0.480	0.417	-0.011	-0.113	-0.392	1	
FDI	-0.377	0.101	-0.144	-0.137	0.036	-0.320	-0.136	0.529	0.577	0.245	-0.482	1

Appendix Table 2. Pesaran Cross-Sectional Dependency, Westerlund (2007) Cointegration and Pesaran–Yamagata (2008) Slope Homogeneity Results

Variable	CD-Test	CD2-Test	Cointegration		Slope Homogeneity	
CO_2	57.76***	2363.41***	Gt	-2.158**	Δ	7.856***
Methane	126.74***	3780.81***	Pt	-11.424**	ΔAd	11.339***
ICTGE	5.23***	1096.79***	Ga	-4.755**		
ICTGI	34.04***	1321.72***	Pa	-3.289**		
R&D	1.07**	553.21***				
PN	0.60**	590.09***				
PR	4.23***	599.47***				
Indus (GDP)	4.08***	1482.20***				
Indus (current)	-1.15**	1260.60***				
GDP	58.17***	2586.03***				
POP	140.77***	4027.40***				
FDI	-0.77**	1467.10***				

Appendix Table 3. Panel Unit Roots Results

	CIPS	TREND	CADF	TREND	CIPS	TREND	CADF	TREND
	Level				First Difference			
CO2	-2.488**	-2.392**	-2.141**	-2.044**	-4.735***	-4.948***	-3.077***	-3.268***
Methane	-2.307***	-4.153***	-1.379**	-1.742**	-5.647***	-5.943***	-1.820**	-2.551**
ICTGE	-2.634**	-3.180**	-2.297**	-2.961**	-5.164***	5.200***	-4.124***	-4.199***

ICTGI	-2.906*	-3.319*	-2.434***	-2.812**	-5.109***	-5.218***	-3.997**	-4.167**
R&D	-4.373***	-4.509***	-3.153***	-3.130***	-5.939***	-6.092***	-4.639***	-4.565***
PN	-4.061**	-4.218**	-2.804***	-2.960**	-5.874***	-6.015***	-4.606***	-4.632***
PR	-4.296**	-4.503**	-3.421**	-3.722***	-5.839**	-5.839**	-4.850**	-4.872**
Indus (GDP)	-3.434***	-3.812***	-2.360***	-2.853***	-5.642***	-5.723***	-4.024***	-4.007***
Indus (current)	-2.858***	-3.421 ***	-1.466**	-2.156**	-5.912***	-6.012***	-3.436***	-3.448***
GDP	-1.741**	-1.851**	-1.918**	-2.132**	-3.854***	-4.239***	-2.818***	-3.258***
POP	-1.375*	-1.553*	-2.609**	-2.541**	-1.481**	-1.741**	-2.028**	-2.719**
FDI	-2.365***	-2.652**	-2.087**	-2.539**	-4.793***	-4.875***	-3.775***	-3.874***