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TECHNOLOGY INNOVATION AND CARBON EFFICIENCY IN AFRICA: WHAT IS THE ROLE OF DIGITALIZATION AND DIGITAL INCLUSIVE FINANCE?

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Abstract. Improving carbon efficiency and mitigating carbon emissions is fundamental to sustainable development and the well-being of human society. Yet, no study highlighted and identified the drivers of carbon efficiency in Africa. Specifically, an empirical study on the role of technological innovation (GTI), digitalization, and digital inclusive finance (DIF) in improving carbon efficiency (CEE) in Africa is rare. To fill this gap, this study investigates the synergistic impact of green technological innovation (GTI), digitalization, and digital inclusive finance (DIF) on improving carbon efficiency (CEE) from the African perspective. A meta-frontier slack-based environmental polluting technology and mixed integer-valued data envelopment analysis (DEA) is framed to gauge the carbon efficiency across oil-endowment and non-oil-endowment African countries from 2010 to 2019. The results indicate that only a few African countries appeared to be operating at efficient production levels. The bootstrapped regression results indicated an invented U-shaped nexus is established between carbon efficiency and African economic development via the extended stochastic impacts by regression on population, affluence, and technology (STIRPAT) framework. Internet usage and mobile cellular subscriptions as components of digitalization positively improve Africa's carbon efficiency. Mobile money transaction innovation (i.e., active mobile money agents per 1000 km^2) as a dimension of digital inclusive finance conserves Africa's environmental efficiency. Green technological innovations did not drive carbon efficiency significantly in Africa and the two groups. Based on the empirical findings, pragmatic policy strategies are further discussed to boost carbon efficiency and mitigate environmental degradation in Africa.

Keywords: sustainable development, carbon efficiency, digitalization, digital inclusive finance, green technological innovation, DEA, Africa.

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1. Introduction

One of the most pressing challenges that appeared with increasing industrialization in the 20th century is the expanding anthropogenic carbon dioxide (CO_2) emissions (Zhai et al., 2024; Barišauskaitė & Mikalauskienė, 2025), leading to global warming and ecological degradation. This global environmental issue is getting worse and ultimately raising legitimate social concerns. As a result, the "United Nations Sustainable Development Goals (SDGs)" advocates for all economies to transit to low-carbon energy sources and improve energy-related carbon efficiency as critical growth milestones for the world economy. Despite these sound efforts by the United Nations and other international bodies towards mitigating emissions, fossil fuel energy use continues to rise in developed and developing worlds, resulting in environmental degradation and health challenges (Adom, 2019; N'Drin et al., 2022). Although the African subregion contributes minimally to global carbon emissions levels, the climate-related crisis in Africa is monumental (Sai et al., 2023).

Improving carbon efficiency by strategically promoting its positive determinants while working to reduce its negative ones is critical to attaining green growth and carbon mitigation, thereby boosting sustainable development (Song et al., 2024). It also facilitates the mitigation of the climate crisis by transitioning to cleaner manufacturing and consumption. Promoting green technological innovation, digitization, and digital inclusive finance are critical mechanisms for achieving SDGs and improving carbon efficiency via promoting green growth, conserving energy input use, and mitigating environmental pollution. However, the role of these critical sustainable development indicators is not properly addressed when discussing the African economic perspective. Thus, it is essential to investigate the joint role of the above elements in improving carbon efficiency from a developing African economies perspective to help reshape the debate on the appropriate policy recommendations for attaining carbon neutrality and sustainable development.

The study aims to address three critical research issues in the African sustainability literature. First, what is the level of carbon efficiency in Africa? Second, what is carbon efficiency heterogeneity between oil and non-oil-endowed African economies? Third, how do technological innovation, digitalization, and DIF impact carbon efficiency in Africa? Exploring these research questions offers substantial theoretical and empirical relevance. Indeed, to the best of our knowledge, no prior study has comprehensively tackled these critical questions in Africa, which creates a substantial research gap. Past efficiency studies on the African continent have mainly measured energy efficiency (Ohene-Asare et al., 2020) and green productivity (Amowine et al., 2024; Shen et al., 2022), ignoring carbon efficiency and its determinants. The African subregion is susceptible to climatic shocks due to its vulnerabilities to climate change, thus putting it in the spotlight for studies of this nature. However, there is a paucity of studies exploring carbon efficiency and its drivers from the African perspective. Specifically, a comprehensive study on the nexus between green technological innovation, digitalization, DIF, and carbon efficiency is paramount to attaining carbon neutrality and SDGs. Yet, a unified study analyzing the synergistic impact of these critical elements in mitigating carbon emissions from the African perspective is still rare. Therefore, to fill this research gap, a panel dataset of 35 African countries from 2010 to 2019 is adopted to investigate the joint effect of green technological innovation, digitalization, and DIF on carbon efficiency from the African perspective, which may assist in policy formulation. First, an environmental production technology and mixed integer-valued DEA framework are developed to gauge carbon efficiency. Then, several econometric models are adopted to look at the outcomes of technological innovation, digitalization, and DIF on Africa's carbon efficiency. This allows us to ascertain if these linkages correspond with sustainable development goals (SDGs).

The contributions and relevance of the present study, particularly in Africa, can be summarized in several points. First, unlike prior studies that applied the traditional models, this study is the first to propose a meta-frontier slack-based measure (SBM) framework that accounted for both undesired output factors and mixed integer-valued datasets within the polluting technology framework to estimate carbon efficiency across oil-endowed and non-oil-endowed African countries – implying that the new models overcome the inherent challenges associated with classic DEA models. Additionally, our study departs from conventional DEA studies in Africa by looking at the role of polluting technology and mixed integer values in the dataset, which offers a new theoretical contribution to efficiency studies in Africa. This provides a more intuitive understanding of the activities of undesirable output and mixed integer-valued data in efficiency estimation. Empirically, our contribution moves away from existing ones that neglected the role of social dimensions of sustainability and the heterogeneous characteristics of African economies. This study grouped the selected African economies into oil-endowed and non-oil-endowed countries. It incorporated several social measures into the model, offering an in-depth understanding of environmental efficiency in Africa. Finally, this study provides novel perspectives on African countries' quest for low-carbon transition. Understanding carbon efficiency and its driving factors across African countries is an effective way to attain a win-win situation of economic growth and carbon reduction targets, thereby aiding in achieving carbon neutrality drives. Prior studies have ignored how the heterogeneous impact of technological innovation, digitalization, and DIF impacted carbon efficiency. The role of green technological innovation, digitalization, DIF, and other carbon efficiency driving factors are essential in promoting sustainability. Indeed, this study offers theoretical and practical contributions that can be adopted to reinforce policy frameworks and eventually improve environmental sustainability. Thus, estimating carbon efficiency and assessing its drivers in African countries is relevant. The empirical findings offer an in-depth discussion of the interplay among green technological innovation, DIF, digitalization, and carbon efficiency. Understanding these issues may help policymakers develop resilient carbon reduction policies relevant to "Agenda 2063" and SDGs.

The rest of this study is structured in the following fashion: Section 2 contains a literature review on carbon efficiency and green technological innovations. Section 3 describes the meta-frontier data envelopment analysis and data used. Section 4 presents the results. Section 5 concludes and offers policy implications related to achieving carbon efficiency gains.

2. Literature review

This study investigates how digitalization, digital finance, and green technological innovation influence carbon efficiency from a developing African perspective. The relevant literature is classified into two main groups: the initial part discusses insights into how CEE is measured. Second, we present essential literature on how the three variables of the study impacted carbon efficiency.

2.1. Carbon efficiency estimation

Carbon emission efficiency (CEE) is a critical indicator in the quest for a drive for a low-carbon economy and attaining sustainable development. Some scholars contended that it denotes achieving substantial economic growth while reducing the carbon factor or the extent to which manufacturing processes diverge from the production frontier. Scholarship efforts on CEE primarily fall under the following strands. First, prior studies typically adopt the single-factor index to explain CCE, which several scholars and industry players have fiercely debated. They contend that the single-factor index only denoted some aspects of CEE and ignored incorporating several critical production inputs on CEE, such as labor, capital, and energy use factors. In the spirit of the above, the total-factor index was introduced by (Zhou et al., 2010), which accounted for several inputs and output factors. Given the urgent need for environmental sustainability, the research effort to achieve the SDGs must incorporate economic, social, and environmental factors in measuring carbon efficiency (Alkurdi et al., 2024). From a methodological viewpoint, several approaches have been developed to estimate CEE. Currently, researchers mainly adopt the parametric and the non-parametric frameworks to evaluate CEE in the existing literature. In the case of the parametric framework, the stochastic frontier analysis (SFA) is frequently employed, which requires the specification of the underlying production frontier in advance (Adom, 2019). The non-parametric relies on the mathematical DEA framework (Amowine, 2023; Ohene-Asare et al., 2020).

The DEA framework is used in this study due to its inherent capabilities to accommodate several inputs and several output cases (Amowine et al., 2024). The DEA is most suitable for measuring country-level carbon efficiency as it does not require the specification of a predetermined functional form when specifying the underlying production frontier. The carbon efficiency was measured for the BRICS economies by Wang and Huang (2023) and among the OECD economies by (Lee et al., 2023). The carbon efficiency of the circular economy in China was estimated by (Xu et al., 2021). The carbon efficiency of the global economy was investigated by (Dong et al., 2022; Wang et al., 2023). Regarding Africa's context, no study has estimated the carbon efficiency across oil-endowment and non-oil-endowment African countries. While this contribution acknowledged existing of relatively few efficiency studies on the African continent (Amowine, 2023; Amowine et al., 2019, 2020, 2021; Ohene-Asare et al., 2020), none of these studies modeled carbon efficiency and its drivers; specifically, by accounting for the joint role of mixed integer values and undesirable output in the model. Importantly, Africa is home to some countries with huge quantities of oil endowment. Exploiting these natural elements is fossil fuel intensive, leading to carbon emissions, which imperil environmental sustainability. Yet, prior studies failed to account for this important heterogeneity characteristic of African countries. Thus, our study developed a meta-frontier SBM model that accounted for this heterogeneous feature of African countries-oil-endowment and non-oil-endowment, substantially improving the limited efficiency studies in Africa. Moreover, most scholars believe that measuring carbon efficiency is one of the most innovative ways of decoupling environmental pressures from economic growth, which aids in achieving sustainable development. However, in Africa's case, no study has investigated the joint role of GTI, digitalization, and DIF in boosting carbon efficiency on the continent. Investing in and monitoring the progress of these critical indicators is crucial to improving environmental sustainability in the developing world.

2.2. Digitalization and carbon efficiency

The concept of the digital economy represents several ways through which governments, business firms, and the individuals of a nation utilize digital technologies. Lately, daily operations across different domains have been impacted by the surge of such technologies as big data, artificial intelligence, and the internet. A steep trend related to the uptake of aforementioned technologies has been seen in Africa. It has become an integral part of the intrinsic dimension of the African economy's drive for competitiveness and sustainable development. Several scholars have investigated the influence of digitalization in promoting sustainable development with varying impacts across economies. First, the positive effects of digitalization on the ecosystem facilitate the decarbonization, dematerialization, and demobilization effects, which mitigate carbon emissions through less energy usage (Alam & Murad, 2020; Ma et al., 2022). Moreover, Saia (2023) emphasized that there are two distinct approaches concerning the information communications technology (ICT) – emissions nexus – "green ICT" and "ICT for green." The first view is about the ecological effect that should be abated (direct effects) via smart production and making ICT more environmentally friendly, which can be attained by minimizing fossil fuel usage by hardware, data centers, and data-driven processes, and adopting renewable energy sources, thereby eliminating electronic waste generations. The second view (i.e., "ICT for green") is that increasing the use of digital technologies is a vital vehicle that enhances environmental sustainability (indirect effect). In this case, digitalization can be used as a mechanism to boost the efficiency of the transmission, utilization, and production of electricity, thus fostering environmental quality.

Empirically, digitalization substantially improves environmental quality by optimizing energy use structure, boosting innovation, and reshaping the industrial system (Hao et al., 2022; Wang et al., 2022a; Zhang et al., 2022). It aids to eliminates CO_2 emissions intensity by enhancing innovation, raising the share of renewable energy, and improving energy efficiency and green growth (Wang et al., 2022a; Wang & Zhong, 2023; Yan et al., 2023). The digital economy and GTI concept are robust instruments for boosting carbon efficiency (Zhao et al., 2022a). In addition, Wang et al. (2022b) and Yi et al. (2022) emphasized that the digital economy may mitigate the carbon factor via spatial effects. Conversely, the earlier literature also assumes that the digital economy may appear detrimental to environmental quality (Dong et al., 2022). The primary rationale behind this observation is that digital products such as computers are energy intensive, increasing the energy demand (Ma et al., 2022), and their application may lead to environmental deterioration. The proliferation of digital centers may raise energy use, affecting the environment (Jahangir et al., 2021). Finally, links between digitalization and carbon emission may be nonlinear (e.g., quadratic), Saia (2023). A critical outlook of the literature survey established that the digitalization-carbon emissions nexus has yielded mixed findings and is far from consensus. Moreover, the influence of digitalization in promoting carbon efficiency from the African perspective is lacking. Using African data, this study checks the impact of GTI, DIF, and digitalization on carbon efficiency via the environmental Kuznets curve (EKC) framework, thus addressing the research gaps in Africa.

2.3. Digital inclusive finance and carbon efficiency

As digital inclusive finance (DIF) has developed substantially, it has shifted the boundaries of conventional financial inclusiveness and has turned into a crucial factor for boosting sustainable development. However, in the digitalization era, the role of Internet finance cannot be ignored in the sustainability debates, especially in developing economies. Internet development has brought about global information sharing, unlocking the financial sector's frontiers of knowledge and innovation. The Internet availability rendered serious changes in the financial sector, leading to an increased uptake of digital inclusive finance (Cheng et al., 2023). Manyika et al. (2016) emphasized that digital finance leverages internet technology to offer financial services for the less privileged to reduce poverty among these vulnerable groups. The DIF substantially improves income levels, minimizes income inequality between urban and rural dwellers, and significantly improves the financial system's stability (Buchak et al., 2018).

Empirically, relatively few past studies examined DIF – carbon emissions nexus, with mixed conclusions. First, some studies suggest that DIF efficiently and effectively reduces environmental pollution. Shahbaz et al. (2022a) observed that DIF substantially reduces carbon emissions to a more significant degree than changes in energy mix simply because of the asymmetric effect of DIF on CO_2 emissions. Dong and Yao (2024), Wang and Guo (2022) asserted that DIF is useful in mitigating urban carbon emissions in China. Similarly, Zhang and Liu (2022) indicated that the synergistic impact of DIF and green innovation substantially improves carbon emissions efficiency. Sun et al. (2023) revealed that DIF has a significant sustainable effect and aids in reducing the intensity of carbon emissions. Le et al. (2020) indicated that by integrating with green technology investment, DIF substantially reduces environmental pollution. Cao et al. (2021) also claimed that DIF improves energy environmental efficiency. Yu et al. (2022) also supported the view that DIF aids in curbing environmental degradation. In contrast, some studies suggest that the DIF may lead to carbon emissions. Wang et al. (2022c) noted a direct link between DIF and carbon emission due to increasing affluence. Pu and Fei (2022) investigated the influence of DIF on residential CO_2 emissions and suggested that DIF exacerbates households' CO_2 emissions. Zhao et al. (2021) indicated that promoting DIF offers an avenue for new enterprises to gain access to financial support, which would eventually lead to a rise in energy consumption by these new business firms and, thus, increase environmental pollution. Frankel and Romer (1999) believed that improved DIF led to higher consumer consumption ability and adversely increased utilization of fossil fuel-intensive products, eventually putting pressure on the environment. Finally, the literature reported that the technological effect of DIF exhibits some significant spatial influence on mitigating carbon emissions (Bu et al., 2024; Wang & Guo, 2022; Wang et al., 2022c). The literature review establishes that digital finance follows no decisive connection with CO_2 emissions, which warrants further investigation. Furthermore, the effect of DIF on carbon efficiency needs to be given more attention in the African sustainability literature. Therefore, we fill this research gap by investigating the impact of DIF on carbon efficiency from the African viewpoint, which enriches the theoretical and empirical literature and serves as a guiding document for policy formulation to improve environmental governance.

2.4. Green technology innovation and carbon efficiency

Green technological innovation (GTI) is critical to promoting high-quality sustainable development. GTI adheres to the principle of economics and facilitates conserving energy and production resources via innovation spillovers (Jiakui et al., 2023; Song et al., 2022). It substantially reduces environmental pollution and ecological deterioration (Sharma et al., 2021) and certifies minimal undesirable externalities rendered by technological innovation (Liu et al., 2022). GTI facilitates attaining SDGs, effectively allocating resources, and conserving environmental resources (Qu & Liu, 2022). Thus, GTI is critical in improving environmental quality and fostering sustainable development (Bai et al., 2020).

Empirically, Dauda et al. (2021) established that GTI could potentially curb carbon emissions in some selected African countries from 1990 to 2016. In the same view, Ibrahiem (2020) reported that GTI substantially mitigates carbon emissions in Egypt. Among the BRICS, Khan et al. (2020a) demonstrated that GTI effectively and efficiently mitigates carbon emissions. Khan et al. (2020b) argued that GTI helps decrease the degradation of the environment in the case of G7 economies. In OECD countries, Hashmi and Alam (2019) reported that GTI, in the form of patents, reduces carbon emissions. Also, Wang et al. (2021) and Luo et al. (2022) claimed that GTI aid in improving green productivity in China, which helps in the fight against climate change. Godil et al. (2021) also noted a link between GTI and renewable energy, curbing carbon emissions in China's transportation sector. Meanwhile, some studies, however, stated that GTI can potentially lead to adverse effects on the environment. Khattak et al. (2020) observed that GTI negatively impacted environmental sustainability in China, Russia, and South Africa, while the reverse is the case for Brazil. A study by Du et al. (2019) illustrated that the mitigating powers of GTI were absent in low-income countries but are in effect in affluent economies. In the G20 economies, Erdoğan et al. (2020) reported that innovation in the infrastructure sector adversely affects environmental quality. The final group of studies suggests technological innovation has some spillover influences among the surrounding regions (Jiakui et al., 2023; Zhang & Liu, 2022), which may boost regional eco-efficiency. Others focused on green investment and corporate social responsibility (Brescia et al., 2024). However, the influential effect of GTI on Africa's carbon efficiency has not been investigated.

In summary, the literature survey reveals that the role of GTI in mitigating carbon emissions is mixed. The findings of these studies are inconclusive and thus warrant further investigation involving this critical indicator. Besides, no study has examined the link between GTI and carbon emissions efficiency in the African context in the literature. Thus, this study contributes to the debate by investigating the synergistic effect of green technological innovation, digitalization, and digital inclusive finance on carbon efficiency in Africa. This substantially helps to steer the green economic development and ensure sustainable development in Africa.

3. Methods

This Section focuses on introducing a new assessment framework via the renounced DEA statistical technique for measuring the performance of decision-making units. This modeling framework aids producers in making informed decisions, leading to reducing environmental pollution and promoting sustainable development. However, the classic DEA models fail to account for the polluting technology persistence effect, mixed integer values, and disparities in production technologies. The above limitations have rendered the application of the traditional models useless. Therefore, we improve upon the classic DEA model herein in this study. Integrating the mixed integer concept, the slack-based framework Tone (2003), the oriented-SBM model Tone (2001), and the O'Donnell et al. (2008) meta-frontier framework, this study developed an improved meta-frontier SBM models to measure carbon efficiency in Africa. The presented models substantially overcome the inherent challenges associated with the conventional DEA and offer a more robust estimation of carbon efficiency results. This modeling technique substantially makes our study innovative and different from the few existing African studies.

3.1. Production technology

This study aims to construct a meta-frontier framework for measuring the carbon efficiency of African countries based on unintended environmental output (carbon emissions) and to account for integer-valued data. To achieve this, the presented DEA models will be based on the oriented SBM frameworks (Tone, 2001). We extended these models by incorporating unintended output factors under the polluting technology and accounted for integer-valued data when establishing the mathematical programming problem.

Furthermore, the first step in DEA modeling is setting the production technology function for a holistic analysis. Production technology explains the nature of the competitive environment in which manufacturers operate. African economies differ regarding regions, management types, and resource allocation. To capture the role of this heterogeneous environment in which African economies work, the meta-frontier is typically adopted to reflect the differences among the underlying production technologies. Then, all African economies are further subdivided into groups according to their technological differences.

Suppose there are n African economies; each country is a DMU with production factors. The input metrics are split into two distinct factors – real and integer inputs denoted by $x^R \in \mathbb{R}_+^{m_1}, x^I \in \mathbb{Z}_+^{m_2}$, and the two intended output vectors are grouped – real and integer outputs represented by $y^R \in \mathbb{R}_+^{s_1}, y^I \in \mathbb{Z}_+^{s_2}$. The metrics for the unintended traditional and unintended integer outputs are defined as $b^R \in \mathbb{R}_+^{p_1}, b^I \in \mathbb{Z}_+^{p_2}$, respectively. Thus, the production possibility set (PPS) of the improved SBM framework is expressed as follows:

$$PPS^{SBM} = \left[(x^R, x^I, y^R, y^I, b^R, b^I) \middle| \begin{array}{l} \sum_{j=1}^{n} x_j^R \lambda_j \le x^R, \sum_{j=1}^{n} x_j^I \lambda_j \le x^I, \sum_{j=1}^{n} y_j^R \lambda_j \ge y^R, \\ \sum_{j=1}^{n} y_j^I \lambda_j \ge y^I, \sum_{j=1}^{n} b_j^R \lambda_j \le b^R, \sum_{j=1}^{n} b_j^I \lambda_j \le b^I, \\ \sum_{j=1}^{n} \lambda_j = 1, \lambda_j \ge 0, \forall j \end{array} \right]. \quad (1)$$

In the spirit of Eq. (1), the PPS for the improved meta-frontier SBM framework was built in this study to reflect the different production technologies as follows:

$$PPS^{Meta-SBM} = \left[(x^R, x^I, y^R, y^I, b^R, b^I) \middle| \begin{array}{l} \sum_{g=1}^{G} \sum_{j=1}^{n} x_{gj}^R \lambda_{gj} \le x^R, \sum_{g=1}^{G} \sum_{j=1}^{n} x_{gj}^I \lambda_{gj} \le x^I, \sum_{g=1}^{G} \sum_{j=1}^{n} y_{gj}^R \lambda_{gj} \ge y^R, \\ \sum_{g=1}^{G} \sum_{j=1}^{n} y_{gj}^I \lambda_{gj} \ge y^I, \sum_{g=1}^{G} \sum_{j=1}^{n} b_{gj}^R \lambda_{gj} \le b^R, \sum_{g=1}^{G} \sum_{j=1}^{n} b_{gj}^I \lambda_{gj} \le b^I, \\ \sum_{g=1}^{G} \sum_{j=1}^{n} \lambda_{gj} = 1, \lambda_{gj} \ge 0, \forall j \end{array} \right]. \quad (2)$$

3.2. Improved meta-SBM framework

In the spirit of the undesirable SBM Tone (2003) and the oriented-SBM model Tone (2001), integer requirements and bad output factors are adequately included in the classic model's constraint function and objective function via polluting technology. Technically, by effectively integrating mixed integer-valued data and unintended output factors, the study's improved SBM model can be written as follows (Zarrin, 2023):

$$\delta_o^{SBM*} = \min \frac{1}{1+\frac{1}{m_1+m_2+s_1+s_2+p_1+p_2}\left(\sum_{i_1=1}^{m_1}\frac{t_{i_1}^{R-}}{x_{i_10}^R}+\sum_{i_2=1}^{m_2}\frac{t_{i_2}^{I-}}{x_{i_20}^I}+\sum_{r_1=1}^{s_1}\frac{w_{r_1}^{R+}}{y_{r_10}^R}+\sum_{r_2=1}^{s_2}\frac{w_{r_2}^{I+}}{y_{r_20}^R}+\sum_{u_1=1}^{p_1}\frac{z_{u_1}^{R-}}{b_{u_10}^R}+\sum_{u_2=1}^{p_2}\frac{z_{u_2}^{I-}}{b_{u_20}^I}\right)} \tag{3}$$

$$\begin{aligned}
\text{s.t.}\ & \sum_{j=1}^{n} x_{i_1j}^R\lambda_j = x_{i_10}^R - t_{i_1}^{R-}, \quad i_1 = 1,\ldots.,m_1,\\
& \sum_{j=1}^{n} x_{i_2j}^I\lambda_j \leq \tilde{x}_{i_20}^I, \quad i_2 = 1,\ldots.,m_2,\\
& \tilde{x}_{i_20}^I = x_{i_20}^I - t_{i_2}^{I-}, \quad i_2 = 1,\ldots,m_2,\\
& \sum_{j=1}^{n} y_{r_1j}^R\lambda_j = y_{r_10}^R + w_{r_1}^{R+}, \quad r_1 = 1,\ldots.,s_1,\\
& \sum_{j=1}^{n} y_{r_2j}^I\lambda_j \geq \tilde{y}_{r_20}^I, \quad r_2 = 1,\ldots.,s_2,\\
& \tilde{y}_{r_20}^I = y_{r_20}^I + w_{r_2}^{I+}, \quad r_2 = 1,\ldots,s_2,\\
& \sum_{j=1}^{n} b_{u_1j}^R\lambda_j = b_{u_1j}^R - z_{u_1}^{R-}, \quad u_1 = 1,\ldots.,p_1,\\
& \sum_{j=1}^{n} b_{u_2j}^I\lambda_j \geq \tilde{b}_{u_20}^I, \quad u_2 = 1,\ldots.,p_2,\\
& \tilde{b}_{u_20}^I = b_{u_20}^I - z_{u_2}^{I-}, \quad u_2 = 1,\ldots,p_2,\\
& \sum_{j=1}^{n} \lambda_j = 1,\\
& t_{i_1}^{R-} \geq 0, w_{r_1}^{R+} \geq 0, z_{u_1}^{R-} \geq 0,\\
& t_{i_2}^{I-} \geq 0, w_{r_2}^{I+} \geq 0, z_{u_2}^{I-} \geq 0,\\
& \tilde{x}_{i_20}^I, \tilde{y}_{r_20}^I, \tilde{b}_{u_20}^I \text{ integer.}
\end{aligned}$$

where t_i^{R-} and t_i^{I-} represent the slacks linking to real input and mixed-integer input excesses. The slacks associated with the desired output-mixed integer output shortfall are captured by ($w_{r_1}^{R+}$ and $w_{r_2}^{I+}$), while the unintended-mixed integer output excesses are denoted by ($z_{b_1}^{R-}$ and $z_{b_2}^{I-}$). In computing the efficiency estimates, model (3) expands the desired mixed integer output metrics while contracting the unintended mixed integer output to determine whether a DMU_0 is on the efficient frontier or not. Furthermore, the above model (3), DMU_0 operates on the efficient frontier when all slacks are associated with desirable and the bad outputs within the mixed integer are zero. Otherwise the investigated DMU_0 is inefficient.

The Model (3) was built with the assumption that all decision-making units (DMUs) operate with the same technology. However, in practice, DMUs operate with different resource types, regional differences and disparities in economic development. Specifically, African economies might have disparities in production technology due to heterogeneity in oil-resources types. Thus, following O'Donnell et al. (2008), this contribution divides African economies into G technology-heterogeneous classes to account for these disparities. Hence, the study adopted the meta-frontier DEA framework due to the heterogeneous nature of African economies. The study's improved meta-frontier SBM model can be built as follows:

$$\delta_o^{SBM} = \min \frac{1}{1+\frac{1}{m_1+m_2+s_1+s_2+p_1+p_2}\left(\sum_{g=1}^{G}\sum_{i_1=1}^{m_1}\frac{t_{u_1}^{R-}}{x_{i_1 0g}^{R}}+\sum_{g=1}^{G}\sum_{i_2=1}^{m_2}\frac{t_{u_2}^{I-}}{x_{i_2 0g}^{I}}+\sum_{g=1}^{G}\sum_{r_1=1}^{s_1}\frac{w_{r_1}^{R+}}{y_{r_1 0g}^{R}}+\sum_{g=1}^{G}\sum_{r_2=1}^{s_2}\frac{w_{r_2}^{I+}}{y_{r_2 0g}^{R}}+\sum_{g=1}^{G}\sum_{u_1=1}^{p_1}\frac{z_{u_1}^{R-}}{b_{u_1 0g}^{R}}+\sum_{g=1}^{G}\sum_{u_2=1}^{p_2}\frac{z_{u_2}^{R-}}{b_{u_2 0g}^{R}}\right)}$$

$$\begin{aligned}
\text{s.t.} &\sum_{g=1}^{G}\sum_{j=1}^{n} x_{i_1 jg}^{R}\lambda_{jg} = x_{i_1 og}^{R} - t_{i_1}^{R-}, \quad i_1 = 1,....,m_1, \\
&\sum_{g=1}^{G}\sum_{j=1}^{n} x_{i_2 jg}^{I}\lambda_{jg} = \tilde{x}_{i_2 og}^{I}, \quad i_2 = 1,....,m_2, \\
&\tilde{x}_{i_2 og}^{I} = x_{i_2 og}^{I} - t_{i_2}^{I-}, \quad i_2 = 1,...,m_2, \\
&\sum_{g=1}^{G}\sum_{j=1}^{n} y_{r_1 jg}^{R}\lambda_{jg} = y_{r_1 og}^{R} + w_{gr_1}^{R+}, \quad r_1 = 1,....,s_2, \\
&\sum_{g=1}^{G}\sum_{j=1}^{n} y_{r_2 jg}^{I}\lambda_{jg} = y_{r_2 og}^{I}, \quad r_2 = 1,....,s_2, \\
&\tilde{y}_{r_2 og}^{I} = y_{r_2 og}^{I} + w_{r_2}^{I+}, \quad r_2 = 1,...,s_2, \\
&\sum_{g=1}^{G}\sum_{j=1}^{n} b_{u_1 jg}^{R}\lambda_{jg} = b_{r_1 og}^{R} - z_{u_1}^{R-}, \quad u_1 = 1,....,p_1, \\
&\sum_{g=1}^{G}\sum_{j=1}^{n} b_{u_2 jg}^{I}\lambda_{jg} = \tilde{b}_{u_2 og}^{I}, \quad u_2 = 1,....,p_2, \\
&\tilde{b}_{u_2 og}^{I} = b_{u_2 jg}^{I} - z_t^{I-}, \quad u_2 = 1,...,p_2, \\
&\sum_{g=1}^{G}\sum_{j=1}^{n} \lambda_{jg} = 1, \\
&t_{i_1}^{R-} \geq 0, w_{r_1}^{R+} \geq 0, z_{u_1}^{R-} \geq 0, \\
&t_{i_2}^{I-} \geq 0, w_{r_2}^{I+} \geq 0, z_{u_2}^{I-} \geq 0, \\
&\tilde{x}_{i_2 og}^{I}, \tilde{y}_{r_2 og}^{I}, \tilde{b}_{u_2 og}^{I} \text{ integer.}
\end{aligned} \tag{4}$$

Based on the estimated outcomes from the Eqs. (3)–(4), this study further measured the technical gap ratio (TGR) to reflect how to improve the carbon efficiency potential in Africa. The technical gap ratio (TGR) under the concepts of the meta-frontier must not be more than the efficiency under the group frontier. Mathematically, the ratio between the two frontiers can be expressed as:

$$TGR = \frac{\delta_o^{SBM}}{\delta_o^{SBM*}}, \tag{5}$$

where, δ_o^{SBM} and δ_o^{SBM*} represents the meta-fronter and the group production frontier efficiency of the under-investigated African countries.

3.3. Determinants of carbon efficiency in Africa

3.3.1. STIRPAT model

This study employs the STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) model to investigate the influence of contextual variables on carbon efficiency in Africa for the first time. The STIRPAT econometric framework is developed from the IPAT model by Ehrlich and Ehrlich. The IPAT framework is presented as:

$$I = P \times A \times T, \tag{6}$$

where I, P, A, and T stand for human impact on ecology, population, affluence, and technology, respectively. Although the IPAT framework has contributed substantially to understanding human influences on the environment, it has some inherent drawbacks. It assumes that the nexus between human activities and the atmosphere is linear, which makes its usage problematic. Several scholars have substantially modified and improved the basic IPAT framework (York et al., 2003). However, not all the variants must readily follow the "non-monotonic or non-proportional" influence of the driving forces. In this paper, we adopt the STIRPAT framework, which has more flexibility relative to the other variants. Mathematically, the classic STIRPAT framework is written as follows:

$$I_{it} = \alpha P_{it}^{b} A_{it}^{c} T_{it}^{d} \varepsilon_{it}, \tag{7a}$$

where, the ecological impact, I, depends on the size of the population (P), affluence (A), and technology (T); α captures the intercept. Meanwhile, a, b, and c are elasticities linked to P, A, and T, respectively. ε denotes the error term. Subscripts i and t represent country and time. To account for the role of additional variables, the conventional STIRPAT framework can be extended as follows:

$$I_{it} = \alpha P_{it}^{b} A_{it}^{c} T_{it}^{d} Z_{it}^{e} \varepsilon_{it}. \tag{7b}$$

The STIRPAT framework has been omnipresent in studies investigating the influence of contextual variables on eco-efficiency. Some of these studies extended the classic STIRPAT framework by incorporating many variables as a proxy to understand their environmental impact. Following the earlier literature, we adopt the STIRPAT framework to study the effect of digitalization, digital finance, and technological innovation on environmental efficiency in Africa. The empirical model is constructed as follows:

$$\begin{aligned} CEE_{it} &= \alpha_0 + \beta_1 \ln GDP_{it} + \beta_2 (\ln GDP_{it})^2 + \beta_3 \ln GTI_{it} + \beta_4 \ln DIG_{it} + \beta_6 \ln DIF_{it} + \\ &\beta_7 \ln REC_{it} + \beta_8 \ln DI_{it} + \beta_9 \ln FDI_{it} + \varepsilon_{it}. \end{aligned} \tag{8}$$

Furthermore, to account for the disaggregated effect of both digitalization and digital finance, Eq. (8) can further be extended as follows:

$$\begin{aligned} CEE_{it} &= \alpha_0 + \beta_1 \ln GDP_{it} + \beta_2 (\ln GDP_{it})^2 + \beta_3 \ln GTI_{it} + \beta_4 \ln FBS_{it} + \beta_5 \ln FTS_{it} + \\ &\beta_6 \ln IUI_{it} + \beta_7 \ln MCS_{it} + \beta_8 \ln DIFR1_{it} + \beta_9 \ln DIFR2_{it} + \beta_{10} \ln DIFA1_{it} + \beta_{11} \ln DIFA2_{it} + \\ &\beta_{12} \ln REC_{it} + \beta_{13} \ln DI_{it} + \beta_{14} \ln FDI_{it} + \varepsilon_{it}, \end{aligned} \tag{9}$$

where CEE captures the corrected bootstrapped carbon efficiency as measured by the DEA framework. The variable GDP and its square term represent the influence of economic development on carbon efficiency. GTI indicates green technology innovation. Fixed telephone subscribers (FBS), Fixed telephone subscribers (FTS), Individuals using the internet (IUI), and mobile cellular subscriptions (MCS) denote the components of digitalization. The four dimensions of mobile money transactions innovation, i.e., registered agent 1 (DIFR1), registered agent 2 (DIFR2), active agents 1 (DIFA1), and active agents 2 (DIFA2), as proxy variables for digital inclusive finance in Equation (9). REC symbolizes renewable energy share. DI and FDI signify domestic and foreign direction investments, respectively. α_0, t, and ε_{it} represents fixed effect, time period and the disturbance term, respectively. All variables are used in logarithmic form.

3.3.2. Truncated bootstrapped regression

The efficiency estimates computed by the DEA approach are truncated due to the nature of the model and, thus, do not follow a normal distribution. Thus, using the classic ordinary least squares (OLS) to measure the influence of contextual variables on efficiency estimates may suffer from bias (Amowine et al., 2021). Past African studies typically adopted multiple and Tobit regression frameworks to examine the effect of driving factors on eco-efficiency. Indeed, Simar and Wilson (2007) observed that efficiency estimates obtained from the DEA model are serially correlated and render bias in estimation. Using the Tobit and multiple regression frameworks might result in inaccurate conclusions. The truncated bootstrapped regression technique is thus recognized as a robust approach to dealing with the above shortcomings. Therefore, this study employs truncated bootstrapped regression to investigate the role of digitalization, digital finance, and technological innovation in the context of Africa's carbon efficiency.

3.4. Variable selection and data sources

3.4.1. Dependent variable

The improved DEA framework presented in Section 3.1 is adopted to compute the carbon emission efficiency (CEE), which serves as the dependent indicator of the model. The inputs and outputs used in this study were chosen subject to data availability and existing literature (Amowine et al., 2024). Unlike the earlier literature in the domain of Africa, the two-input metrics employed in this study are traditional and integer input factors. Two output variables were also adopted – the desirable output metric is GDP, and the integer output indicator is HDI. The undesirable environmental pollution output indicator is carbon emissions.

3.4.2. Core explanatory variables

Digital inclusive finance (*DIF*). At present, there is no standard statistic for this newly introduced concept. The existing literature essentially divides this DIF indicator into three distinct groups. First is the digital financial development index built by the "crawler software" for searching and displacing new data on the internet, which is challenging to collect and analyze (Zhang & Liu, 2022). The second approach was developed by Peking University and Ant Financial Service Group, accounting for digitalization, breadth of coverage, and the depth of usage of China's financial system (Cao et al., 2021; Zhang & Liu, 2022). Thirdly, the DIF is also measured by mobile money transaction technology innovation, which provides a platform for the vulnerable to access digital transactions and helps shape the lives of the less privileged in developing economies (Asongu et al., 2023). The DIF, as it relates to technological innovations, may also contribute to energy conservation and mitigation of climate change. Due to data availability issues, and by following Asongu et al. (2023), the present study uses the four dimensions of mobile money transactions innovation, i.e., registered agent 1 (DIFR1), registered agent 2 (DIFR2), active agents 1 (DIFA1), and active agents 2 (DIFA2), as proxy variables to measure the impact of DIF on carbon efficiency in Africa.

Digitalization (*DIG*). In the sustainability literature, digitalization is a critical indicator for promoting the green development agenda. Regarding measuring digitalization, some studies, such as (Shahbaz et al., 2022b) and (Saia, 2023; Zhao et al., 2022b), adopted an index system via the principal component analysis to develop a digitalization index. However, the index system may mask the role of certain individual factors of digitalization in promoting carbon efficiency (Zhao et al., 2022a). Thus, given the availability of the data, this study examines the influence of digitalization using the disaggregate approach (i.e., individual using internet (IUI), mobile cellular subscriptions (MCS), fixed broadband subscribers (FBS), and fixed telephone subscribers (FTS) as the four components of digitization) on carbon efficiency in Africa.

Green technological innovation (*GTI*). The international patent categorization of green patents (IPC) instituted by the "World Intellectual Property Organization (WIPO)" and the number of green patents is typically adopted to measure GTI. Indeed, the conventional GTI has a broad meaning, and it is hard to precisely gauge the green input and output components of such an index. Several scholarships have identified GTI as a valuable indicator for mitigating carbon emissions and achieving carbon neutrality. Thus, by following Sakariyahu et al. (2023), this study employs an index that comprises (see Appendix Table A2) as a proxy indicator for GTI.

3.4.3. Control variables

Following the principles relevant to the Environmental Kuznets Curve (EKC) and the STIRPAT framework, this study selected other critical variables as control variables. These control variables are rather diverse and describe socioeconomic and environmental development aspects. GDP per capita (PGDP) to capture the effect of economic development on carbon efficiency. Specifically, this study uses logged PGDP to measure economic development. In the spirit of EKC, the square terms of PGDP were added to the analysis to validate or otherwise the EKC hypothesis. Renewable energy (REC) depicts the share of renewable energy in total final energy consumption. Improving carbon efficiency in Africa requires massive investment in renewable energy and optimizing its usage to control environmental pollution. The available literature suggests REC helps to alleviate environmental stress (Amowine et al., 2024). The study innovatively added foreign direct investment (FDI) and domestic investment (DI) into the model to understand the role of the two indicators in influencing carbon efficiency on the continent.

3.5. Data used

The empirical study applies a balanced panel of 35 African countries, consisting of 20 oil-endowment African countries and 15 non-oil-endowment African countries from 2010 to 2019. This period is known as the "era of mass digitalization," where the proliferation of the internet became more pronounced. Due to data unavailability issues, some African countries were excluded from the sample. The dataset was acquired from multiple sources such as the US Energy Administration, the Penn World Table, and the World Bank's development indicators databases. The definition of all variables used and the contextual variables are all disclosed in this study (see supplementary Appendix Table A2 for details). Essentially, the study adopts four input metrics and three output factors to analyze African carbon efficiency. Capital, energy consumption, and labor (employees) are the traditional input metrics, while the duration of compulsory education (social indicator) is used to capture the integer input. The traditional output metric is gross domestic product (GDP), and the integer output metric is the human development index (HDI). Carbon emissions are considered as the undesired output factor.

Based on IMF's statistics, African countries can be categorized into oil-endowed and non-oil-endowed African countries (see details in the supplementary material). With this classification, how these countries operate regarding economic development and environmental management differs across oil-endowed and non-oil-endowed groups in Africa – implying the presence of heterogeneous characteristics among the sampled African economies in this study. Importantly, no study in the existing literature on the African continent has adopted this categorization to measure CCE in Africa. Thus, following the IMF's classification for oil-endowment and non-oil-endowment, we employ this framework to account for the heterogeneity in Africa. Past studies that neglected this critical heterogeneous feature may not present accurate policy advice to policymakers on the continent. Appendix Tables A1–A3 display the list of African countries investigated, the definition of the study's variables, and abbreviations used, respectively. Table 1 contains the average estimates of the study's descriptive statistics across the African heterogeneous features.

Table 1 illustrates that the average estimates of the energy input are higher in the oil-endowment African countries (OEAC), which substantially translates into higher average CO_2 emission values relative to the non-oil-endowment African countries (NOEAC) and Africa. Implying prior studies that failed to consider the heterogeneous nature may miss this critical phenomenon on the continent. Thus, carbon emissions mitigating policies are necessary to foster the growth of emissions relevant to energy use in Africa. The average estimates of the other variables (i.e., employees, HDI, capital, ecological footprint, and energy input) appeared to be lower in NOEAC compared to pool and OEAC. The OEAC's economic output is more pronounced relative to NOEAC, demonstrating that oil resource extraction substantially aids in distinguishing between the two classes of African countries. Table 2 presents the descriptive statistics of the factors of carbon efficiency in Africa.

Table 2 shows that the averages of per capita GDP are higher in OEAC, followed by Africa and NOEAC. On digitalization, all the components show that OEAC had more investments in digital technologies compared to NOEAC and Africa. The mean values of digital financial inclusion appeared to be highest in the NOEAC, followed by OEAC and Africa. On green technological innovation, the statistics indicate that NOEAC performs relatively better than Africa and OEAC on average. Thus, African authorities are urgently advised to prioritize investing in these digital technologies to boost the digital economy and conserve the environment. Improving digital technologies, GTI and DFI, aids in promoting environmental quality since these elements have little negative externalities on the environment. The mean values of the other indicators follow a similar pattern in this study.

Table 1. Averages of input and output variables

Variable	Type	OEAC	NOEAC	Africa	notation
Energy use (10^{10})	Input	17170	560	8630	x_{ij}^{R}
Capital (10^{6})	Input	810410	92990	441450	x_{ij}^{R}
Employees (10^{4})	Input	129.51	55.64	91.52	x_{ij}^{R}
Duration of compulsory education	Integer input	8.618	7.878	8.237	x_{ij}^{I}
Gross domestic product (GDP) (10^{6})	Desirable output	255450	37040	143130	$y_{r_1 j}^{R}$
Human development index	Integer output	0.583	0.516	0.549	$y_{r_2 j}^{I}$
Carbon dioxide (CO_2) emissions	Undesirable output	1.580	0.515	1.032	$b_{u_1 j}^{R}$

Table 2. Averages of contextual variables

Type	Variable	OEAC	NOEAC	Africa
Explained indicator	CEE	0.648	0.872	0.739
Core explanatory indicators	FBS	1.35	0.44	0.88
	FTS	3.17	1.75	2.44
	IUI	25.25	13.83	19.38
	MCS	87.94	79.93	83.82
	DIFR1	58.05	116.95	88.34
	DIFR2	35.79	109.43	73.66
	DIFA1	106.40	217.70	163.63
	DIFA2	61.68	176.60	120.79
	GTI	–0.041	0.039	–8.57E-10
Control indicators	PGDP	2685.41	1495.70	2073.56
	REC	50.56	70.52	60.82
	DI	23.68	20.56	22.08
	FDI	4.21	4.64	4.43

4. Empirical results

This section adopts the improved meta-frontier SBM developed in Section 3.2 to gauge the carbon efficiency performance across the oil-endowment and non-oil-endowment African countries. Then, several econometric frameworks are used to investigate the influence of technology innovation, digitalization and DIF on carbon efficiency performance.

4.1. Analysis of Africa's carbon efficiency estimates

The estimated results of CEE of the 35 African countries from 2010 to 2019 are shown, and we will thoroughly discuss the characteristics of the CEE performance based on different perspectives in this part of the study.

4.1.1. Africa's CEE characteristics

The proposed DEA framework (Eq. 4) measures meta-frontier (global) carbon efficiency in Africa from 2010 to 2019. Table 3 and Figure 1 present the findings of global carbon efficiency in Africa. Figure 1 demonstrates the total global average carbon efficiency trend across the study's periods.

Table 3 shows that the findings are remarkable and interesting since some African countries are far from having an efficient frontier. Overall, the average efficiency estimate for Africa is 0.739, which indicates that the sampled African countries are not on the efficient frontier.

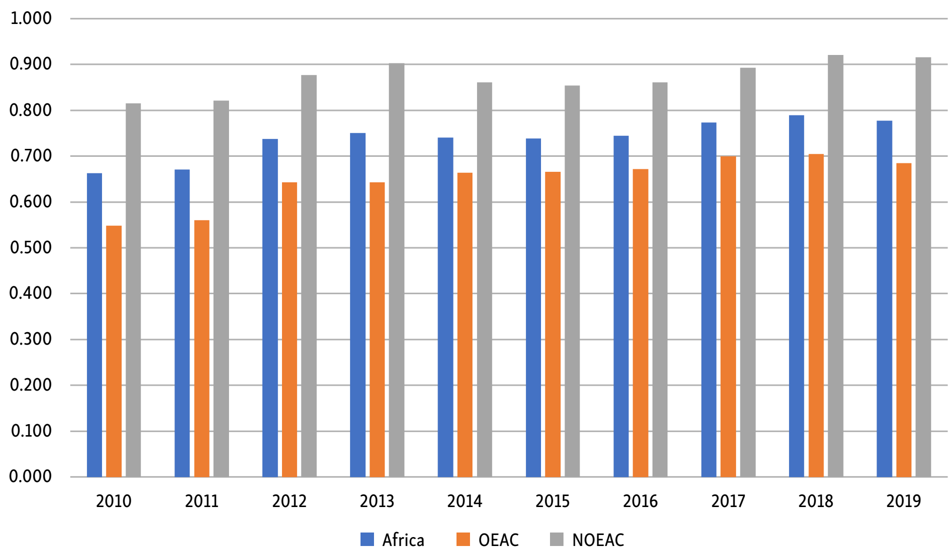

Figure 1. Trends in the mean global carbon efficiency in Africa

Table 3. Average trend of overall global carbon efficiency index in Africa

Years	Oil-endowment African countries (OEAC)	Non-oil-endowment African countries (NOEAC)	Africa
	SBM-OEAC	SBM-NOEAC	SBM-Africa
2010	0.548	0.816	0.663
2011	0.560	0.821	0.671
2012	0.642	0.877	0.738
2013	0.643	0.903	0.751
2014	0.663	0.861	0.740
2015	0.666	0.854	0.738
2016	0.672	0.861	0.745
2017	0.700	0.893	0.773
2018	0.705	0.921	0.790
2019	0.684	0.916	0.777
Mean	0.648	0.872	0.739

This finding can be compared to Jiang et al. (2024), who investigated carbon efficiency and its drivers in China. Furthermore, Figure 1 clearly shows the existence of heterogeneity among the investigated groups based on the global efficiency analysis. Comparing the estimates between the two classes based on the overall global mean efficiency, it appears that NOEAC had relatively superior efficiency estimates than OEAC and Africa. These findings underscore the crucial role of African policymakers and international policy agencies such as the International Renewable Energy Agency (IRENA) and Sustainable Energy for Africa in instituting policies to improve carbon efficiency on the continent. The overall mean trend could further be improved through more investment in renewable energy sources and via improved technology upgrades, which could substantially contribute to the overall carbon efficiency of the African continent.

4.1.2. Results of different groups CEE characteristics

The meta-frontier framework explicitly described in Section 3 is used to estimate the group efficiency of carbon efficiency in Africa. The resulting outcome of the group efficiency is clearly illustrated in Figure 2.

The results of the group efficiency analysis are displayed in Figure 2, which indicates the annual mean trend of carbon efficiency in Africa from 2010 to 2019. Figure 2 shows significant disparities in carbon efficiency among the two distinct groups of African countries, with the highest average estimates in NOEAC followed by OEAC and Africa. This finding collaborates with Amowine et al. (2024), who also revealed that the effect of carbon emissions on efficiency is more pronounced in African countries with abundant natural resources. This means that oil-endowment African countries (OEAC), despite their resource richness, lack the ability to achieve improved economic development and carbon efficiency. They have sufficient resource dependence and uneconomic production systems, resulting in high-energy

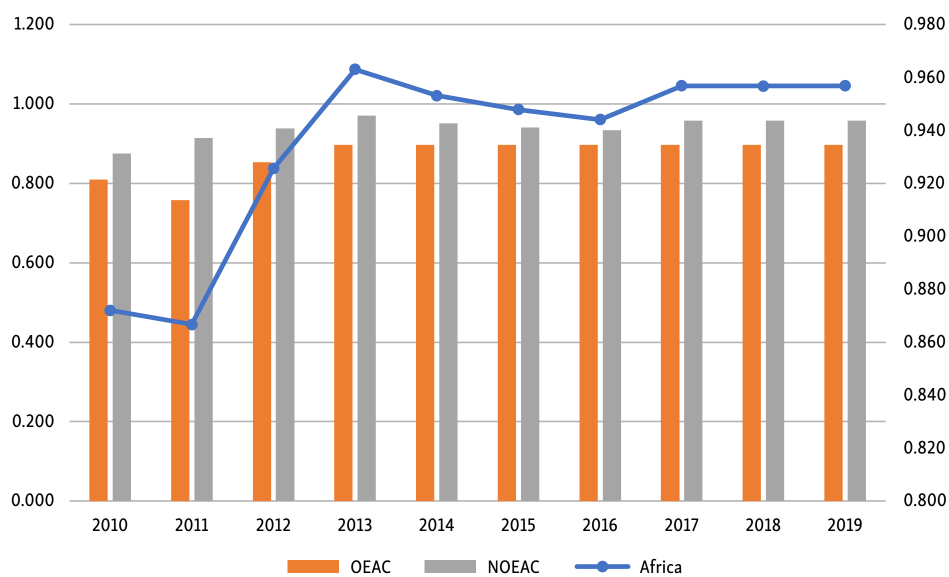

Figure 2. Trends in mean group carbon efficiency measures in Africa

utilization, high-polluting generation ventures and low efficiency. Thus, ecosystem fragility and unsustainable development paradigms exist in most African countries. Implementing carbon emissions reduction strategies and proper environmental management (particularly in the oil-producing industries) would aid improved economic growth, thus boosting carbon efficiency on the continent. The research underscores the need for the African continent as a whole to prioritize a green development agenda and improve the existing technologies to attain sustainable development.

4.1.3. Technology gap ratio (TGR) results

The TGR allows one to compare the efficient levels of the group frontier to those at the pooled frontier, thereby quantitatively assessing the performance gaps for different groups of countries. Table 4 presents the estimated results of the TGR.

Table 4. Results of TGR across the classes in Africa

Group	Mean TGR	Max	Min	Standard deviation
OEAC	0.718	0.749	0.677	0.023
NOEAC	0.866	0.912	0.824	0.028
Africa	0.794	0.833	0.766	0.022

Table 4 demonstrates that the overall average of the technology component was inefficient, indicating that the estimated TGR values across the two classes of African countries were 0.718 (OEAC), 0.866 (NOEAC) and 0.794 (Africa). The TGR describes the potential ability of energy-use technology and the availability of technology to improve carbon efficiency, and a greater TGR estimate portrays a higher potential ability for carbon efficiency technology. Notably, the estimated TGR values in the NOEAC are far better than those of the OEAC in Africa. These findings call for more attention by policymakers on the continent to improve technology and adopt more advanced technologies to mitigate carbon emissions and reshape the continent towards sustainability.

4.2. Baseline regression results

The present study explores the synergistic impact of digitalization, digital inclusive finance (DIF), and green technological innovation (GTI) on carbon efficiency while controlling for economic development, renewable energy, domestic investment, and foreign direct investment in developing African perspectives. The regression approach expatiated in the "method section" is adopted for the regression analysis. The resulting outcomes are given in Table 5.

Table 5 presents the estimates of bootstrapped regression, taking into consideration possible nonlinearity. Based on the EKC hypothesis, the baseline regression model investigated the heterogeneous effects of digitalization, DIF, and GTI on African carbon efficiency.

The regression analysis estimates suggest that two out of the four parts of digitalization (i.e., internet use and mobile cellular subscriptions) exhibit a positive and statistically significant link to carbon efficiency in Africa (see Table 5). This finding is supported by Wang et al. (2022b), who looked into the role of digital economy on environmental sustainability in China. The other components of digitalization (i.e., fixed broadband – and fixed telephone subscriptions) were estimated to be statistically insignificant in this study. This indicates that digitalization explicitly aids in addressing the SDGs. In the spirit of reducing carbon, digitalization exerts an essential role in boosting innovation and industry and advancing infrastructure, facilitating the development of a sustainable society, and contributing to climate change mitigation while strengthening the shift towards a cleaner energy mix. For these reasons, the study findings suggest that African governments should make more efforts to streamline the development of digital infrastructure and improve the intensity and usability of digitalization that facilitates the attainment of the SDG-13 goals by increasing environmental awareness on the continent. Improving access to advanced ICT infrastructure and the Internet (SDG-9) will ultimately enhance the 5G network, e-commerce, and the promotion of high-tech industries, boosting resource allocation and reducing environmental pollution on the continent.

Table 5. Carbon efficiency (CEE) effects by the bootstrapped truncation regression

Variable	(1)	(2)	(3)
lnPGDP	0.0773*** (0.1816)	0.0328*** (0.1736)	0.0182** (0.1645)
$(\ln PGDP)^2$	–0.0538*** (0.0123)	–0.652*** (0.394)	–0.076*** (0.1108)
lnGTI	–0.00013 (0.0078)		–0.0037 (0.0091)
lnFBS		0.0105** (0.006)	–0.0074 (0.0062)
lnFTS		0.0374*** (0.008)	0.0403*** (0.0086)
lnIUI		0.0512*** (0.0117)	0.0604*** (0.0134)
lnMCS		0.0716 (0.243)	0.0497* (0.045)
lnDIFR1			0.00486 (0.0127)
lnDIFR2			–0.0142 (0.0145)
lnDIFA1			–0.0135 (0.01215)
lnDIFA2			0.0222* (0.0132)
lnREC			0.0249** (0.008)
lnDI			0.0158*** (0.005)
lnFDI			–0.0195*** (0.006)
Prob>chi^2	0.000	0.000	0.000
Obs.	350	350	350

Note: *, **, and *** signify statistical significance levels at 1%, 5%, and 10%, respectively. Standard errors in parentheses.

Digital finance (only component 4) had a significant positive and beneficial link with carbon efficiency in Africa, indicating that the development of digital finance platforms will substantially aid in mitigating carbon emissions and reducing environmental pressure (Wang & Guo, 2022). Improving the DIF has several benefits. First, DIF is often applied in retail operations, such as in the service industry, which may lead to a reduced household footprint. Second, introducing DIF services encourages financial equity and the availability of services across different strata of society, leading to increased activities by enterprises operating in rural areas. These rural enterprises usually show well-established indigenous technology, low energy use and minimal environmental pressures. Thus, the development of the DIF will not only boost the financial standing of these industries but also mitigate carbon emissions and improve the operations of those enterprises. The DIF is pivotal in upgrading small and medium-sized industries that usually benefit less from conventional financial systems. The agricultural sector can be an example of the positively affected rural businesses (IPA, 2017). Thus, African governments are advised to provide an environment enabling the DIF (i.e., in the form of mobile money innovation) to grow on the continent.

The truncated bootstrapped regression findings established that green technological innovation had an insignificant effect on CEE in the African subregion. This finding implies that the positive mitigating effect of scientific research and development, patents, and trademarks on CEE was not significant in Africa. These conclusions are confirmed by earlier studies (Du et al., 2019) reporting that the emission abatement effect of GTI is unfavorable in developing economies. The green technological innovation and research and development (R&D) investment resources in Africa are among the least in the world, and their development has not yet grown substantially for the past decade, which affected its contribution to boosting CEE in Africa. In addition, the number of green patents granted, green trademark applications, and other utility model patent registrations are lower in Africa compared to the world, which explains the lack of significant outcomes. These findings point towards improving GTI to enhance efficiency and attain environmental quality. Capital investment, improving R&D expenditure, and encouraging talent development are essential elements to upgrade green technology innovation. To conserve the environment, renewable energy technology, clean production enterprises, and green intelligent industries are necessary avenues to promote a modern Africa. This approach will ultimately enhance effective resource allocation, contributing to a low-carbon economy drive.

The findings on the effects of the control variables indicate that the linkage between economic development and carbon efficiency is positive and significant. The square term of economic development had a negative statistically significant correlation with CEE. This indicates that the Kuznets curve hypothesis is supported (Jiang et al., 2024). Most existing studies adopt a linear framework to investigate the linkage between efficiency and economic development. However, the process of economic development is complex and may not always follow a simple linear relationship. Thus, the finding of this contribution is unique since the nonlinear modeling approach was adopted and further offers evidence of an invested U-shaped Kuznets curve in Africa. The share of renewable energy is also positive and statistically significant, providing evidence that renewable energy usage aids in curbing carbon emissions in developing economies (Amowine et al., 2024). The influence of domestic investment is positive and correlates with CCE in Africa, while foreign direct investment showed a significantly negative association with CEE in the African continent. This finding suggests the "pollution halo" effect is established for FDI in Africa.

4.3. Heterogeneity analysis

The African continent is home to countries with oil deposits that place these countries among the world's top oil-producing economies. Countries with large quantities of oil resources are seen as having a better economic outlook, indicating that countries blessed with oil resources differ from those without these resources in Africa. However, in the literature, several studies have reported the "resource curse" syndrome and the unsustainable development nature of countries with oil deposits. Importantly, environmental pollution challenges and waste utilization of these resources are reported to be associated with oil-endowment economies in the developing world. Inferring from the above, the role of different oil-resource types may influence the impact of digitalization, DIF, and GTI on CEE differently across these groups of African countries. Thus, we divide the sample into oil-endowment and non-oil-endowment African economies to explore the disparities in the role of the key variables in the model. Table 6 shows the estimates obtained during the heterogeneity check.

From Table 6, we observed that green technological innovation (GTI) exhibited a negative statistical significance in NOEAC; however, it was insignificant in OEAC. This indicates Africa is backward in green innovation development and calls for more attention to improve GTI on the continent to help mitigate environmental squalors in Africa. The contribution of three digitization components (FTS, IUI, and MCS) has a significant positive effect on efficiency in OEAC, while the others are insignificant. In the NOEAC, we find that FBS, IUI, and MCS positively correlate with carbon efficiency, while other components have a negative significant association with carbon efficiency. These findings are unsurprising since some countries are characterized by poor digital infrastructure development and other acute developmental challenges hampering the smooth economic transformation. Also, the subregion is the worst regarding technology upgrades compared to the developed world. Thus, decision-makers are advised to make huge investments in digital technology development and upgrading technology will further boost the continent's efficiency. In digital finance, we find that all four components are insignificant across the groups in this study. Thus, it is important to accelerate and leverage digitalization to build a sophisticated digital finance platform to improve environmental governance.

As regards the control variables, the linkages between CEE and economic development exhibited in NOEAC are inverted U-shaped. However, the EKC is not valid in OEAC. The latter results coincide with Amowine et al. (2024) for Africa. Finally, domestic investment and the share of renewable energy positively correlate with carbon efficiency in OEAC and NOEAC. These findings suggest that African countries must strengthen regional coordinated development and prioritize green and sustainable development to achieve carbon neutrality on the continent.

Table 6. Heterogeneity test and the bootstrapped truncated regression

Variable	OEAC	NOEAC
lnPGDP	0.9801*** (0.1616)	0.1588*** (0.2725)
$(\ln PGDP)^2$	–0.0618*** (0.0108)	–0.0765*** (0.0186)
lnGTI	–0.0135 (0.0095)	–0.0151 (0.0147)
lnFBS	0.00851 (0.0077)	–0.0420*** (0.0076)
lnFTS	0.049*** (0.012)	0.0567*** (0.0110)
lnIUI	0.0355*** (0.0101)	0.0715*** (0.01801)
lnMCS	0.0716** (0.0310)	–0.066* (0.0367)
lnDIFR1	–0.0024 (0.014)	–0.00513 (0.0285)
lnDIFR2	0.0006 (0.014)	–0.0013 (0.0313)
lnDIFA1	–0.0087 (0.0098)	0.0057 (0.0293)
lnDIFA2	–0.0065 (0.01098)	0.01115 (0.0317)
lnREC	0.011* (0.0067)	–0.0299 (0.0469)
lnDI	0.0179** (0.0067)	0.0192*** (0.0073)
lnFDI	–0.028*** (0.0067)	–0.0546*** (0.0122)
$Prob>chi^2$	0.000	0.000
Obs.	170	180

Note: *, **, and *** signify statistical significance levels at 1%, 5%, and 10%, respectively. Standard errors in parentheses.

4.4. Robustness test

It is essential to check if the results rendered by regression analysis are not artifacts of convolutions of multiple (hidden) factors that can be mistakenly attributed to the independent variables in the regression model. The implications stemming from the regression estimates should be stable across different contexts in order to reliably claim them as those genuinely describing the underlying behavior of economic agents. The robustness analysis carried out in this research involves two-fold considerations. First, the key explanatory variable is changed in line with Liu et al. (2023). Specifically, a robustness check involves substituting PGDP with GNIPC and re-estimating the bootstrap truncated regression. Second, the estimator is changed, and following Luo et al. (2021) and Jiang et al. (2024), this study also adopts the Tobit regression as a robustness check. Table 7 shows the estimates of regression with GNIPC across different subsamples. Similarly, the results for the Tobit model are displayed in Table 8.

The resulting estimates indicate that the significant effect of digitalization, DIF, and green technological innovation on carbon efficiency in Africa remains the same as noted in the baseline regression. The robustness check findings also show that the invested U-shaped Kuznets curve is still valid in Africa. These outcomes are in line with the baseline regression. All in all, the results are robust to the two tests (changes in the variable of interest and estimator).

Table 7. Regression with GNIPC as an independent variable

Variable	Africa	OEAC	NOEAC
lnGNIPC	0.0684*** (0.0174)	0.0631 (0.0417)	0.0653*** (0.0191)
$(\ln GNIPC)^2$	–0.0065*** (0.0022)	–0.0019 (0.0039)	–0.0054** (0.0026)
lnGTI	0.0099 (0.0099)	–0.0027 (0.0102)	0.0121 (0.0144)
lnFBS	–0.00877 (0.0067)	0.00399 (0.0086)	–0.049*** (0.0068)
lnFTS	0.036*** (0.0093)	0.0225** (0.0113)	0.057*** (0.0103)
lnIUI	0.034** (0.0146)	0.043*** (0.0148)	0.037** (0.0176)
lnMCS	0.025 (0.026)	–0.0147 (0.0292)	–0.0623* (0.035)
lnDIFR1	0.0145 (0.014)	–0.0126 (0.0149)	0.0151 (0.0272)
lnDIFR2	–0.0188 (0.015)	0.0149 (0.0157)	–0.0206 (0.0299)
lnDIFA1	–0.014 (0.013)	–0.0088 (0.0113)	0.0039 (0.0283)
lnDIFA2	0.0196 (0.014)	–0.0018 (0.0129)	0.0166 (0.0306)
lnREC	0.021* (0.008)	0.0041 (0.0084)	–0.073* (0.050)
lnDI	0.017* (0.0095)	0.0258** (0.0087)	0.0127 (0.011)
lnFDI	–0.0099 (0.007)	–0.0859** (0.0258)	–0.00091 (0.0071)
Prob>chi^2	0.000	0.000	0.000
Obs.	350	170	180

Note: *, **, and *** indicate statistical significance at 1%, 5%, and 10% levels, respectively. Standard errors are presented in parentheses.

Table 8. Estimates of the Tobit regression

Variable	Africa	OEAC	NOEAC
lnPGDP	0.1617*** (0.1606)	0.9696*** (0.159)	0.154*** (0.279)
$(\text{lnPGDP})^2$	–0.075*** (0.0108)	–0.061*** (0.105)	–0.076*** (0.019)
lnGTI	–0.0035 (0.0088)	–0.013 (0.009)	–0.015 (0.015)
lnFBS	–0.0075 (0.0061)	0.008 (0.007)	–0.042*** (0.0077)
lnFTS	0.0397*** (0.009)	0.035** (0.0101)	0.056*** (0.012)
lnIUI	0.060*** (0.012)	0.069*** (0.013)	0.070*** (0.017)
lnMCS	0.059** (0.013)	0.070** (0.030)	–0.065* (0.035)
lnDIFR1	0.0046 (0.012)	–0.0016 (0.013)	–0.005 (0.028)
lnDIFR2	–0.014 (0.013)	–0.0001 (0.0141)	–0.0017 (0.031)
lnDIFA1	–0.013 (0.011)	–0.009 (0.010)	0.0053 (0.028)
lnDIFA2	0.0215* (0.012)	–0.006 (0.012)	0.012 (0.031)
lnREC	0.025** (0.008)	0.012** (0.007)	–0.032 (0.045)
lnDI	0.015*** (0.005)	0.027*** (0.006)	0.052*** (0.011)
lnFDI	–0.019** (0.006)	–0.017* (0.008)	–0.019** (0.007)
Prob>chi^2	0.000	0.000	0.000
Obs.	350	170	180

Note: *, **, and *** indicate statistical significance at 1%, 5%, and 10% levels, respectively. Standard errors are presented in parentheses.

4.5. Discussion

As previously mentioned, the paper is among the first ones to explore the impact of digitalization, digital inclusive finance, and green technology innovation on carbon efficiency from a developing African perspective, focusing on the period from 2010–2019. The proposed methodological framework uses a novel meta-frontier mixed integer DEA framework to gauge efficiency. The resulting efficiency scores and other drivers are then analyzed using the regression techniques in the second stage. The baseline results indicate that the majority of the countries we studied have departed from the carbon-efficient frontier. These findings align with those of Zhou et al. (2010) and Zheng et al. (2024), measuring carbon performance in China. However, our findings diverge from previous studies that did not consider the role of mixed integer inputs and outputs in efficiency estimation. Moreover, estimating carbon efficiency from the developing African perspective cannot be ignored.

In the second stage, the bootstrapped truncated regression is used to check the effects of the variables of interest while controlling for income (GDP per capita) and other variables via the extended STRIPAT framework. We observed that two components of digitalization correlate with carbon efficiency in Africa, while the rest were estimated to be insignificant. This finding aligns with Wang et al. (2022b) in regard to the effects of the digital economy on curbing carbon emissions. The outcome of this study demonstrates that investing in the components of digitalization would help promote a greener world agenda. This marginal transformation in Africa is driven by the private sector, led by telecommunication companies and the relatively stable growth of North African economies. Analysts believe the African continent is the next frontier for the digital revolution. Notwithstanding, some of the components of digitalization exhibit a negative correlation with carbon efficiency, particularly across the groups. These findings are a wake-up call for African governments to improve the poor and weak digital infrastructure to benefit from the digital revolution fully. Improving the dimensions of digitalization can facilitate a renewable energy transition that aligns with sustainable development. Notably, our study's outcome outperformed prior studies by investigating the disaggregated effect of digitalization on carbon efficiency in Africa for the time. Thus, in contrast to past studies, particularly in Africa, our study's outcome offers a more profound picture of the likely role of disaggregated components of digitalization on carbon efficiency from a developing African perspective. This study accounted for four components of digitalization, which is far superior to what exists in the literature. Our findings are insightful in that policymakers can stimulate the growth of each component compared to the index system. Moreover, this study differs from the existing studies in Africa, which neglect the role of the heterogeneous nature of African countries. The present study grouped these African countries into oil-endowment and non-oil-endowment ones. Further, it investigated the potential role of digitalization across these groups, unlike most past African studies that relied on a weak linear regression framework to check the role of digitalization and other variables. Indeed, the study adopted a more complex and robust modeling technique. This offers a comprehensive understanding of how carbon efficiency is impacted by digitalization across the two classes of African countries, empowering policymakers with targeted strategies.

Furthermore, the importance of digital inclusive finance cannot be neglected. The study's findings established that among the four dimensions of digital inclusive finance used in this research, only one (i.e., DIFA2) correlates with carbon efficiency in the case of Africa. The other three components were estimated to have no significant influence on carbon efficiency. This finding is in line with Wang and Guo (2022), elucidating the position of the digital economy in mitigating carbon efficiency in the case of China. Moreover, comparing our findings with past studies in Africa, our novel results contradict the findings of Asongu et al. (2023), indicating that all four dimensions of mobile money transaction innovation are shaping progress in Africa. Besides, this study is the first to adopt mobile money transaction innovation as a proxy to DIF to measure its effect on carbon efficiency. This novel and irreplaceable indicator capture the potential role of DIF on carbon efficiency for the first time in the case of Africa. Again, most existing studies used the principal component analysis to obtain a relevant composite indicator. Departing from those studies, the disaggregated approach was used by including all four dimensions in the estimation model, accounting for heterogeneity in this study. This is essential as it helps decision-making make targeted policies to improve each component. The implication of the study's findings suggests policy-makers on the continent must have put measures in place to strengthen the digital financial sector, as it has the potential to aid in addressing the climate crisis.

Additionally, green technology innovation is found to have an unsignificant contribution to carbon efficiency in Africa. Unlike prior studies by Obobisa et al. (2022), establishing a positive synergy between green innovation and environmental sustainability in Africa, our findings departed from prior studies' outcomes in the literature. As previously stated, Africa's green innovation is worse than other developed economies. Amidst the chaos and uncertainty on the continent, African governments must scale up and prioritize green technology development by channeling the needed investment resources into improving research and development (R&D) and encouraging other environmentally eco-friendly technologies to foster advanced green innovation development on the continent. Finally, this contribution is the first to offer a broader discussion of the joint role of digitalization, digital inclusive finance, and green technology innovation in environmental sustainability for the developing African context. This substantially contributes to a better understanding of these key variables in promoting the greener world agenda. Unarguably, these insightful findings of this study are a wake-call for African authorities to make substantial investments in improving the digital infrastructure, improving green innovation, and strengthening the digital financial sector, which would inevitably aid in fostering environmental sustainability in Africa.

5. Conclusions and policy implications

The major purpose of this contribution is to develop a robust analytical framework to measure carbon efficiency and its determinants across oil-endowment and non-oil-endowment African countries. In the era of immense environmental deterioration, exacerbated by the cumulative impact of human activities, measuring CEE and its driving factors from the African perspective is necessary. The effects of the climate crisis on the global economy are enormous and far-reaching. Despite contributing less, African economies suffer a disproportionate proportion of the hazards of climate shocks due to their extreme vulnerability. As a result, carbon mitigation pathways offer an enduring solution to avoid climate risk. An important point is mitigating carbon emissions by improving carbon efficiency and taking into account its drivers. Specifically, the role of digital technologies cannot be neglected in the sustainability debate in Africa. In light of this, several studies have identified that green technological innovation boosts environmental quality. Thus, combining the application of digitalization, green technological innovation, and digital financial inclusion offers a more promising avenue for mitigating carbon emissions to promote sustainable development in developing economies. However, the literature on carbon efficiency and its determinants from the African countries' perspective is rare. Accordingly, the present study built a meta-frontier polluting technology and mixed integer-valued data envelopment analysis framework to estimate the carbon efficiency across OEAC and NOEAC in Africa. The bootstrapped regression approach via the extended STIRPAT framework investigates the synergistic influence of digitalization, GTI, DIF, and other determinants of carbon efficiency in Africa.

The empirical outcomes suggest that GTI significantly impedes carbon efficiency in NOEAC, while a similar effect of GTI is not supported in Africa and OEAC. This finding is a wake-up call for authorities on the African continent to improve GTI to attain carbon neutrality targets and boost environmental quality. The four dimensions of digitalization (i.e., internet use and mobile cellular subscriptions) exhibit a positive and statistically significant effect on African carbon efficiency. Moreover, mobile cellular – and fixed broadband subscriptions had the same significant effect on carbon efficiency in OEAC and NOEAC. The other dimensions of digitalization were insignificant, suggesting that African governments should leverage advanced ICT infrastructure and Internet development to achieve carbon neutrality on the continent. Additionally, a noteworthy finding is that renewable energy tends to be conducive to facilitating carbon efficiency in Africa. Among the four dimensions of digital finance, mobile money transactions innovation (i.e., active mobile money agents per 1000 km^2) had a beneficial link with carbon efficiency in Africa, while the other dimensions are observed to be insignificant across OEAC and NOEAC.

There are certain policy implications that can be devised in the light of the empirical results. African authorities should prioritize the development of digital technology infrastructure. Governments should emphasize enhancing the integration and utilization of the digital infrastructure, boosting digital and network production, and improving intelligence capabilities to attain environmental sustainability on the continent. The overall strategies for enhancing digital infrastructure investment should be done by considering each country's economic development level. Leveraging and optimizing regional layout while constructing digital infrastructure is essential in improving economic development and environmental conservation. However, when implementing digital infrastructure development, it is crucial to balance and narrow the gap among the different regional developments and optimize digital resource allocation.

Policymakers on the continent should foster the promotion of digital inclusive finance by improving technological innovation in mobile money transactions. The effective and efficient integration of DIF with digital technology development will accelerate the upgrading of the industrial system, promoting deeper interlinks between productive industries and boosting the transformation of the financial system. The DIF should be supported to offer more inclusive finance avenues to the vulnerable strata of society. Additionally, authorities should grant tax holidays to the emerging DIF sector to enhance economic growth and attain a low-carbon modern society.

Furthermore, more policy efforts should be directed towards improving GTI to gain from the mitigating effect of GTI on the continent. Investing in green innovation and R&D technologies is critical to attaining the knowledge spillover effect and achieving the technology upgrade required to improve carbon efficiency and attain environmental sustainability. Also, policymakers should make and channel budgetary allocations to invest in renewable energy. Other policy avenues that can be exploited to mitigate carbon emissions include implementing stricter environmental regulations and emissions tax. Leverage big data to enhance resource allocation to boost efficiency and productivity on the continent.

Also, it is important to tailor development policies and strategies based on each country's different resource endowments and economic growth levels. As a prominent resource endowment region, Africa can leverage its rich natural resources nature to strengthen economic development and boost green innovation while transitioning to a low-carbon continent. The present study's findings have essential policy significance in attaining the United Nations' SDGs, particularly focused on reducing carbon emissions and supporting environmental sustainability. Hence, governments in Africa should acknowledge and take seriously carbon emission mitigation measures to improve environmental well-being on the continent with the ultimate view of attaining the SDGs.

Finally, our study mainly investigates the impact of GTI, DIF, and digitalization on carbon efficiency, and the study's limitations include the following strands. First, our study primarily focuses on the African perspective, and future research efforts can consider the world economy. Second, due to the non-availability of data, the present research is only limited to 2019. We recommended that the current and updated dataset be used to expand this study when the whole dataset is available. In the future, one can use other advanced DEA frameworks to explore carbon productivity and its drivers in Africa. Other econometric approaches can also be utilized to investigate the effect of the variables of interest on carbon efficiency in Africa.

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APPENDIX

Table A1. List of African countries investigated in the study

Groups	Countries
OPAC	1. Algeria, 2. Angola, 3. Cameroon 4. Congo Republic 5. Congo DR 6. Cote d'Ivoire 7. Egypt 8. Gabon 9. Ghana 10. Morocco 11. Mauritania 12. Malawi 13. Nigeria 14. Niger 15. Sudan 16. South Africa 17. Tunisia
NOPAC	1. Burkina Faso 2. Botswana 3. Eswatini 4. Gambia 5. Guinea 6. Guinea-Bissau 7. Mali 8. Senegal 9. Sierra Leone 10. Togo 11. Kenya 12. Madagascar 13. Mozambique 14. Namibia 15. Rwanda 16. Uganda 17. Zambia 18. Zimbabwe

Table A2. Definitions of indicators used

Models' indicators	Definition	Unit	Source
DEA model			
Capital	Capital stock at constant national price 2017	Million	*PWT*
Compulsory education	Duration of compulsory education	Years	*WDI*
Employees	Number of persons engaged	Million	*WDI*
Energy	Total primary energy consumption	Quad Btu	*EIA*
GDP	Real GDP (2017 US dollar)	Million	*PWT*
HDI	Human development index	Index	*GFN*
Carbon emissions	Carbon dioxide emissions from the consumption of fossil fuels	Metric tons	*WDI*
Econometric model			
CEE	Estimated by the DEA approach		*DEA Model*
DIG	Digitalization		
FBS	Fixed broadband subscriptions		*WDI*
FTS	Fixed telephone subscriptions		√
IUI	Individuals using the internet		√
MCS	Mobile cellular subscriptions		√
DFI	Digital inclusive finance		

End of Table A2

Models' indicators	Definition	Unit	Source
DIFR1	Number of registered mobile money agents per 100,000 adults	–	*FAS*
DIFR2	Number of registered mobile money agents per 1,000 km^2	–	*FAS*
DIFA1	Number of active mobile money agents per 100,000 adults		*FAS*
DIFA2	Number of active mobile money agents per 1,000 km2		*FAS*
GTI	Green technological innovation is measured via the principal component index, which consists of a natural log of scientific and journal articles published, research and development (R&D) expenditure, patent and trademark applications for residents and non-residents, and investment in ICT.	Index	*WDI*
PGDP	Real GDP per capita, (US dollar)	US$	√
REC	Renewable energy share	%	√
DI	Domestic investment	%	√
FDI	Foreign direct investment	%	√

Note: Penn World Table version 10.0 (PWT), World Development Indicators (WDI), Global Footprint Network (GFN) and Financial Access Survey (FAS).

Table A3. List of abbreviations

Acronyms	Full name
DEA	Data envelopment Analysis
CEE	Carbon emissions efficiency
DMU	Decision-making unit
DIF	Digital inclusive finance
GTI	Green technological innovation
STIRPAT	Stochastic impacts by regression on population, affluence, and technology
CO_2	Carbon dioxide emissions
SDGs	Substantial development goals
SBM	Slack-base measure
OEAC	Oil-endowment African countries
NOEAC	Non-oil-endowment African countries
IRENA	International Renewable Energy Agency
ICT	Information communications technology
GDP	Gross domestic product
PGDP	Per capita gross domestic product
TGI	Technology gap inefficiency
EKC	Environmental Kuznets Curve
SFA	Stochastic frontier analysis
TGR	Technology gap ratio
SDGs	Sustainable development goals
WDI	Work bank development indicators
OLS	Ordinary least squares
BRICS	Brazil, Russia, India, China, and South Africa
OECD	Organization for Economic Co-operation and Development