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Digitalization, Energy Use, and Carbon Emission Efficiency: Testing the Digital Paradox

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Abstract

The rapid expansion of digital technologies is reshaping economic and energy systems, but its implications for carbon efficiency remain uncertain. This study examines whether digitalization improves carbon emission efficiency (CEE), investigates the mediating role of green innovation, and tests whether ICTI conditions the digitalization–CEE relationship. Using a panel of 53 economies with varying energy intensities over 2002–2022, CEE is estimated through the Super-Efficiency Slack-Based Measure (SE-SBM), which incorporates energy consumption and carbon dioxide emissions as environmental inputs and undesirable outputs, respectively. Panel-corrected standard errors, Pooled Mean Group, System-GMM, and Driscoll–Kraay estimators are employed for robust inference. The results show that digitalization significantly reduces CEE ($\beta = -0.1677$), indicating that the energy and carbon pressures associated with expanding DII outweigh initial efficiency gains. In particular, the findings suggest that rising electricity and energy demand associated with data centers, communication networks, and ICT-intensive activities can intensify environmental pressure. Green innovation positively improves CEE ($\beta = 0.0089$) and partially mediates the adverse effect of digitalization, although digitalization itself significantly reduces green innovation ($\beta = -0.0820$). Moreover, the digitalization-ICTI interaction is negative and significant ($\beta = -0.6864$), indicating that higher ICTI amplifies the adverse environmental effect of digital expansion. Institutional quality improves CEE, whereas a resource-intensive industrial structure reduces it. A U-shaped relationship between economic growth and CEE is also confirmed. The findings highlight the need for energy-efficient DII, efficient ICT utilization, green innovation, stronger institutions, and sustainable industrial transformation to reconcile digital development with environmental sustainability.

Keywords: digitalization; energy use; carbon emission; green innovation; energy efficiency; environmental sustainability

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1. Introduction

Climate change is closely linked to continued greenhouse gas emissions from energy use and carbon-intensive economic activities. Energy use for electricity generation, manufacturing, transport, and other energy-intensive processes continues to be a significant contributor to carbon emissions. High carbon emissions put pressure on environmental

quality, and sustainable economic development becomes more difficult [1,2]. Despite international efforts, such as the Paris Agreement and Sustainable Development Goals (SDGs), carbon emissions remain a major global environmental concern. Therefore, economies are paying greater attention to reducing emissions and improving the efficiency with which economic output is generated from energy and carbon inputs [3]. This has led to a growing interest in the concept of carbon emission efficiency (CEE), which represents the efficiency of an economy in producing economic output with energy and carbon emissions [4]. The improvement of CEE can be used to assist low-carbon development without a loss of economic activity. As environmental concerns grow, researchers and policymakers are becoming more interested in technological and structural solutions that will help with economic growth while alleviating environmental pressures. Among these solutions, digital transformation has received growing attention as a potential driver of sustainable development.

Digitalization has become an important part of economic transformation and has changed how firms, governments, and households produce, exchange, and use information. Digital infrastructure (DII) can be used to enable real-time tracking, production planning, energy management, online transactions, and data-driven decision-making. These applications can reduce information and transaction costs and help firms identify inefficient use of energy and other resources [5]. Digital technologies can also improve production efficiency and support the adoption of cleaner technologies by improving access to information, knowledge, and technological solutions. Almugren et al. [4] support this positive view by showing that digitalization can improve production efficiency, reduce transaction costs, and facilitate the diffusion of cleaner technologies. Thus, digital transformation can contribute to better resource allocation and more efficient economic activities. These potential benefits have made digitalization an important component of national development and sustainability strategies.

Although these potential benefits are widely recognized, digitalization can also create environmental pressure [5,6]. Digital technologies rely on physical structures, power generation, electronic equipment, data centers, and communication networks. The expansion of this infrastructure can therefore increase energy and material demand [7]. The rising demand for digital services can also generate more electricity use and carbon emissions, especially in countries with carbon-intensive energy supplies [8]. At the same time, digital technologies can improve energy efficiency, optimize production systems, and reduce resource waste through better information processing and decision-making [9–11]. This leads to the digital paradox: digitalization can provide environmental gains and losses simultaneously. The overall effect thus depends on the interplay between the efficiency gains and energy and resource needs of digital expansion.

The digital paradox can be further explained through three related mechanisms. First, the scale effect arises when DII expands across the economy. Electricity, materials, and supporting infrastructure are needed for data centers, communication networks, servers, and digital devices. If carbon-intensive sources are used as the source of energy, environmental pressure can increase as a result of the expansion of DII. Second, the rebound effect arises when a digital technology increases efficiency and decreases production, information, or transaction costs. Reduced costs may attract companies and customers to expand economic and digital use, potentially offsetting some of the initial benefits of efficiency. Third, a factor-crowding-out effect can be present if funds, manpower, and technology are allocated to digital investment rather than green research and development. This may reduce the resources available for green innovation (GI) and weaken its contribution to CEE. The three mechanisms offer a more comprehensive theoretical explanation of how digitalization can contribute to enhancing efficiency in some settings while lowering CEE in others.

However, the environmental effects of digitalization are still inconclusive. Therefore, the above discussion presents the idea that the digitization of technologies can create a 'digital paradox' in which increasing energy demands for digital devices and infrastructure, data transmission, cloud computing, and ICT-related production processes offset the environmental benefits of digital technologies. The potential benefits of digital technologies to increase efficiency and contribute to environmental management can be offset by the rising demand for energy and environmental pressures from the growth of digital networks and digital ICTs in economic activities. In the recent literature, there have been mixed results on the relationship between digitalization and environmental outcomes [6,12,13]. For example, Kwilinski et al. [12], using EU countries for 2006–2020, find that digital inclusion, IT sector contribution, and e-commerce can reduce CO_2 emissions. Alsanie [13] also examines digitalization through resource and energy use and waste reduction, highlighting its potential for sustainability. In contrast, Chen et al. [6] review digitalization in manufacturing and show that its environmental benefits can be accompanied by additional energy and resource requirements. These findings support the view that the environmental effect of digitalization depends on how digital technologies are developed and used. However, they suggest that the environmental effects of digital changes are more complex than originally thought.

Many of these conflicting findings may result from the multidimensional nature of digital development. In the current literature, digitalization is usually measured broadly, which includes DII, internet penetration, and technology adoption [4]. However, these measures mainly capture the availability and diffusion of digital technologies and may not fully reflect the intensity of ICT-related economic activities. Therefore, both digitalization and ICTI represent related but distinct dimensions of digital development. In this study, digitalization refers mainly to the availability, access, diffusion, and development of DII and connectivity across an economy. ICTI, on the other hand, is the intensity and scale of economic activities related to ICTs, such as the production of ICTs, trade in ICTs, the provisioning of digital services, and the economic use of ICT technologies. A country may have broad digital access without having a highly ICT-intensive production or trade structure. Similarly, an economy with a large ICT sector may have substantial ICT-related energy and material requirements [14,15]. Therefore, the need to differentiate between these two dimensions is significant, since broader digital access can lead to an increase in the efficiency of information and production, but a high level of economic activity due to ICT can also generate extra environmental pressures.

The intensity of ICTs can produce both productive and environmental impacts. A higher ICTI can help productivity, information processing, technology upgrading, and more efficient economic activities. However, when ICTI grows and digitalization widens, the environmental burden may also increase. As digital services, the production of ICTs, data processing, and network use grow, more electricity, equipment, and material inputs are needed. Thus, the environmental impact of ICTI could be distinct in relation to the broader digitalization context. The interaction may intensify the environmental costs of digital expansion when greater digital access is coupled with a rapid increase in ICT-related economic activities. This provides a theoretical basis for examining ICTI as a moderating factor rather than treating it only as an independent determinant of CEE.

A further important research gap concerns the mechanism through which digitalization affects CEE. GI can provide an important link between technological development and environmental performance. Digital technologies can support research collaboration, knowledge sharing, information access, and technological innovation [16,17]. These processes can help firms and economies develop and adopt environmentally friendly technologies, improve energy efficiency, and reduce pollution. However, the relationship between digitalization and GI may not always be positive. Digital transformation takes resources, whether

they be financial, human, or technological, and can compete with green research and development when resources are limited. Digitalization may therefore support GI through knowledge and technology diffusion, but it may also crowd out resources for GI. This possibility is relevant because GI can affect energy efficiency, pollution intensity, and CEE. Despite its theoretical importance, the mediating role of GI in the relationship between digitalization and CEE has received limited empirical attention.

Despite these important advances, three major gaps remain in the literature. First, existing studies often treat digitalization as a broad concept and do not clearly distinguish DII and digital access from the intensity of ICT-related economic activities. This distinction is significant because the impact of wider access to the Internet and large-scale production or trade in ICTs or large-scale services could be different. Second, previous studies have not sufficiently examined the mechanism through which digitalization affects CEE. In particular, the transmission channel of 'GI' is still underexplored. Digitalization can facilitate GI through knowledge sharing and technological advancement, but it can also reduce resources for green research and development. Third, limited attention has been given to the interaction between digitalization and ICTI. The analysis of this interaction can reveal whether the impact of digitalization on the environment varies with the increasing intensity of ICT-related economic activities. These gaps motivate an integrated framework that examines the direct effect of digitalization, the mediating role of GI, and the moderating role of ICTI.

This study aims to address these gaps in three main objectives. First, it examines the effect of digitalization on CEE and tests whether digital development generates the digital paradox. Second, it examines whether GI mediates the relationship between digitalization and CEE and determines whether digitalization supports or constrains this channel. Third, it analyzes the moderating effect of ICTI on the relationship between digitalization and CEE. Examining these relationships in conjunction provides a more comprehensive understanding of the relationship between digital development and CEE.

The contributions of this study to the literature can be summarized in three aspects. First, it distinguishes digitalization from ICTI. Availability and diffusion of DII are measured by digitalization, and the scale and intensity of ICT-related economic activities are measured by ICTI. This distinction provides a more detailed view of the environmental consequences of digital development. Second, the study explores how GI acts as a mediating factor between digitalization and CEE. This can be useful for understanding not only whether digitalization impacts CEE but also how it can impact it. Third, it investigates the moderating role of ICTI and assesses whether the environmental impact of digitalization varies with the intensity of ICT-related economic activities. These contributions provide a wider perspective on the digital paradox and its implications for efficiency in carbon emissions.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature and develops the theoretical framework and research hypotheses. Section 3 presents the methodology, including the measurement of CEE, variables, and empirical models. Section 4 reports the empirical results and robustness analysis. Section 5 discusses the main findings in relation to previous research. The conclusions, policy implications, limitations, and directions for future research are provided in Section 6.

2. Review of Literature

2.1. Theoretical Perspectives on Digitalization and Environmental Sustainability

Digitalization and environmental sustainability can be explained through several theories. First, the Porter hypothesis [18] indicates that innovation can help achieve resource efficiency and cleaner production. Digital technologies can help firms use information, energy, and other resources more efficiently. Second, innovation diffusion theory by Rogers [19]

provides a framework for understanding the diffusion of new technologies within firms, sectors, and economies. Digital technologies can support knowledge sharing and the adoption of cleaner technologies. Third, the rebound effect indicates that efficiency gains can drive up economic activity and energy consumption [20]. These theories show why digitalization may have both positive and negative environmental effects.

The above theories provide a basis for understanding the digital paradox. Digitalization can help increase efficiency and contribute to cleaner production. Simultaneously, digital activities can create additional energy and resource demands. Thus, the nature and extent of digital development can influence the final environmental impact.

2.2. Digitalization and Environmental Performance

Digitalization has emerged as a key driver of economic and technological growth. Several studies have reported positive environmental effects. At the microeconomic level, Ren et al. [21] show that digital technologies improve resource use efficiency and production performance. Lyu et al. [22] demonstrate that digital development has a positive effect on the efficiency of the supply chain and the productivity of industries. Wang et al. [23] also demonstrate that digitalization can aid technological innovation, industry upgrade, and resource optimization. Li et al. [24] also find that digital transformation can reduce carbon emissions through efficiency improvements and cleaner production.

Recently, Feng et al. [25] found that digitalization can reduce agricultural carbon emissions by improving resource allocation and production efficiency. Hu et al. [26] demonstrated that DII enables low-carbon development through technological innovation and spatial spillover effects. Digitalization also has a positive effect on the performance of firms, as it lowers external management costs while enhancing internal control [27]. However, this study is concerned with the performance of firms, not environmental efficiency.

The literature also points to the potential of digital technologies to contribute to broader sustainability impacts. Wei et al. [28] concluded that FinTech positively affects ESG performance through financing, innovation, and risk-taking avenues. Qin et al. [29] find that supply chain digitalization improves energy efficiency. Their findings indicate that innovation ability and industrial concentration are significant channels. The positive impact of digital technologies is further supported by these studies. However, they mainly focus on firms, supply chains, or specific digital applications.

Thus, the findings in the literature are compelling that digitalization can enhance efficiency and contribute to environmental sustainability. However, these benefits are not universal. Most studies focus on particular sectors, companies, or digital applications. Less attention has been given to the economy-wide effect of digitalization on CEE.

2.3. Digitalization, Energy Use, and the Digital Paradox

Literature also highlights the possible environmental costs of digitalization. Chen et al. [6] revealed that Industry 4.0 technology can increase the efficiency of resources and information. They also consume energy and materials during their manufacture, use, and disposal and yield electronic waste. Kopp and Lange [30] also showed that digital technologies can improve resource-use efficiency, but the expansion of digital activities may increase energy demand. Meydanoglu and Hurmaci [31] provide further evidence of the link between digital activities and energy use.

Therefore, the evidence is mixed. Kwilinski et al. [12] used data from EU countries from 2006 to 2020 and found that digital inclusion, the IT sector, and e-commerce can reduce CO_2 emissions. In contrast, Chen et al. [6] highlighted the energy, material, and waste pressures linked to digital technologies. Alsanie [13] also examined digitalization through

resource use, energy use, and waste reduction and showed that its sustainability effects depend on the way digitalization is used.

This relationship appears to be context-dependent, consistent with other studies. For example, Santarius et al. [32] explain that efficiency improvements can create additional economic activity and energy use through the rebound effect. The environmental impact of digital transformation also relies on institutions and economies [33]. Therefore, digitalization can have a positive impact on environmental performance in certain contexts and a negative impact in others.

These findings are important to the present study. They showed that digitalization should not be automatically considered beneficial for the environment. They also argue that the impact may vary between economies and stages of digitalization. However, previous studies have not sufficiently examined this issue using CEE as the primary environmental outcome.

2.4. Carbon Emission Efficiency and Its Determinants

The literature also highlights studies focusing on CEE. These studies consider how efficiently economies or sectors generate economic output while using energy and producing carbon emissions. Sun and Huang [34] found an inverted U-shaped relationship between urbanization and CEE in 30 Chinese provinces. Their findings show that the effect of urbanization changes after reaching a certain level. Xiao et al. [35] examined 136 countries and found large differences in CEE across countries and regions. They demonstrated that urbanization, renewable energy, and foreign trade positively affect CEE, while electricity use and INDS negatively affect CEE.

GI is another important determinant of CEE. Dong et al. [36] examine 32 developed countries with carbon neutrality targets. They find that green technology innovation improves CEE. They also found that economic development and urbanization play mediating roles, while financial development strengthens the relationship. Jiang et al. [37] show that the effect of environmental regulation on CEE changes with energy consumption intensity and green technology innovation. Their results confirm that environmental regulation does not have the same effect under all conditions.

Technological progress is also linked to CEE. Xie et al. [38] used data from 59 countries and found that technological progress improves CEE. However, its effects differ across countries with different efficiency levels. They also show that the interaction between technological progress and energy intensity can have different effects.

Recent studies have further supported the importance of innovation and resource allocation. Gao et al. [39] found that carbon emission trading improves carbon efficiency directly and through better labor allocation and green technology innovation. In another study, Gao et al. [40] found that digitalization significantly improves firm performance by reducing external management costs and strengthening internal controls, with a stronger effect observed in state-owned enterprises. Gao et al. [27] show that innovative city policies improve carbon efficiency and create positive spatial spillover. They identified green technology and resource allocation as important channels. These studies show that innovation, institutions, and resource allocation are important for the CEE.

However, most CEE studies focus on traditional factors, such as technological progress, environmental regulation, INDS, urbanization, energy use, and GI. Digitalization has been less discussed as a more comprehensive catalyst for CEE. In addition, existing studies generally do not distinguish DII from the intensity of ICT-related economic activities.

2.5. Digitalization and Green Innovation

Innovation is an important channel through which digitalization affects environmental performance. According to the innovation diffusion theory, digital technologies facilitate knowledge sharing and communication. Steiber et al. [41] and Kumar [42] show that digital technologies can support innovation activities. Liu et al. [43] and Luo et al. [44] also highlight the role of the DII in improving communication, information access, and technology development.

Similarly, Liang and Li [45] and Duan et al. [46] reported that digital transformation enhances innovation by improving research capacity, knowledge sharing, and information accessibility. Digital platforms can also facilitate cooperation among firms and institutions. These processes support the development and diffusion of such technologies.

Recent studies also support the link between digitalization and innovation. Wei et al. [28] identify innovation as an important channel through which FinTech improves ESG performance. Qin et al. [29] conclude that the digitalization of the supply chain boosts energy efficiency, in part, because of innovation capability. These results indicate that digitalization may foster green technological development.

However, the relationship between digitalization and innovation may not always be positive. Digital transformation requires financial, human, and technological resources. In cases where resources are scarce, investment in digitalization may be in competition with resources dedicated to green R&D. Digitalization can then help enable GI by spreading knowledge and technology, but it can also hinder GI by competing for resources.

This issue is important in the present study. Previous research has mainly examined the direct relationship between digitalization and innovation or its effect on firm performance. Limited evidence is available on whether the GI acts as a transmission channel between digitalization and CEE, especially across countries.

2.6. Environmental Governance, Innovation, and Carbon Efficiency

Environmental institutions can also influence the relationship between innovation and environmental performance. Ke et al. [47] found that environmental courts reduce corporate greenwashing. They conclude that there are important channels, such as GI, financing conditions, and media oversight. This suggests that institutional conditions can affect the environmental benefits of innovation.

Similarly, Gao et al. [40] showed that carbon emission trading can improve CEE through green technology innovation and better resource allocation. Gao et al. [27] also concluded that innovative city policies enhance CEE by supporting the use of green technology and resource allocation. These studies indicate that policy and institutional factors can strengthen the contribution of innovation to environmental performance.

However, these studies mainly focus on environmental, institutional, or innovation policies. These factors are not presented in terms of how wider digitalization could interact with them. This leaves an important gap in understanding the relationship between digital development and CEE.

2.7. Research Gaps and Contribution of the Present Study

The previous literature provides useful evidence; however, several gaps remain. First, existing studies provide mixed evidence on the environmental effect of digitalization. Some studies find that digitalization improves efficiency and reduces emissions, while others highlight higher energy use and environmental pressure. This indicates that the impact of digitalization varies and is dependent on the context. Second, previous studies tend to take broad measures of digitalization. They do not clearly distinguish DII from ICT-related economic activities. DII mainly reflects digital access, connectivity, and the spread of digital

technologies. ICTI reflects the scale and intensity of ICT-related production, trade, services, and economic activities. These two dimensions may have different effects on CEE.

Third, there is a lack of research on the role of GI as a channel. Digitalization is known to enhance innovation, as seen in previous studies. However, resource competition can be a constraint for GI. More evidence is therefore needed on whether GI explains part of the relationship between digitalization and CEE. Fourth, the link between digitalization and ICTI is under-researched. An increase in ICTI can contribute to productivity and technological development. However, when it expands together with wider digitalization, it may also increase electricity, equipment, and resource requirements. Examining this interaction can provide a better understanding of the environmental consequences of digital development.

Overall, the literature shows that digitalization, innovation, institutions, and technological development are important for environmental performance and CEE. However, their relationships are predominantly studied separately. In this study, we combine these dimensions in three consecutive steps: first, by investigating the effect of digitalization on CEE; second, by examining the mediating role of GI; and third, by analyzing the moderating role of ICTI. The framework offers a more comprehensive account of the digital paradox and its implications for CEE. Therefore, the following main hypotheses have been specified.

H1. *DII has a negative effect on CEE.*

H2. *DII has a significant effect on GI.*

H3. *GI has a positive effect on CEE.*

H4. *GI mediates the relationship between DII and CEE.*

H5. *ICTI strengthens the negative effect of DII on CEE.*

3. Materials and Methods

SE-SBM is used to measure CEE. It is a non-radial extension of the Data Envelopment Analysis (DEA) framework. The major difference between SE-SBM and radial DEA is that the input slacks and output slacks are taken into account directly in SE-SBM. Thus, it reflects inefficiency in individual inputs and outputs instead of holding to the assumption that all inputs and outputs vary proportionately. The model also allows undesirable outputs to be included directly in the production process.

In this study, CO_2 emissions are treated as an undesirable output. The model seeks to reduce undesirable output and input slacks while maintaining the desirable output. This makes SE-SBM suitable for environmental efficiency analysis. Alternative methods can also be used to measure environmental efficiency. SFA is convenient if a particular form of the production function can be rationalized; however, this requires assumptions regarding the functional form and the distribution of the inefficiency term. These parametric assumptions are not necessary for conventional DEA but may not be appropriate for radial DEA to fully account for input and output slacks. To tackle these problems, SE-SBM employs a non-radial slack-based approach and can incorporate undesirable outputs directly. Therefore, compared with SFA, SE-SBM does not require the researcher to specify a particular production function form or distribution for the inefficiency term. Compared with conventional radial DEA, it provides a more flexible treatment of input and output inefficiencies. The super-efficiency extension also enables efficient decision-making units to be ranked outside the standard efficiency frontier. These features make SE-SBM appropriate for comparing CEE across economies where the production and environmental conditions differ. Thus, SE-SBM is selected as the main measure of CEE.

Multiple inputs and outputs are used to build the SE-SBM framework. Table 1 lists the inputs and outputs that are considered in measuring CEE. The inputs are labor (L), capital (K), and energy (E). GDP is a desirable output, and CO_2 emissions are an undesirable output. L is represented by the total labor force in each economy; capital is proxied by the capital stock; and energy is proxied by total energy consumption.

Table 1. Variable description used for measuring CEE.

Variables	Description	Type	Units	Source
Labor (L)	Total labor force in each economy	Input	No.	WDI
Capital (K)	Capital stock	Input	Dollar	Pen world table
Energy (E)	Renewable and non-renewable energy consumption	Input	MJ	EIA
GDP	Gross domestic product	Desired output	Current US$	WDI
CO_2	CO_2 emission	Undesired output	Kilo	

The model was applied to a balanced panel of 53 economies over 2002–2022. The sample period was selected based on the common availability of the main variables used in the study. In particular, the period provides consistent information for DII, ICT activities, governance, innovation, energy use, capital, labor, GDP, and CO_2 emissions. The year 2022 was used as the final year because it is the latest common year for which a sufficiently complete and comparable set of data was available for all major variables and the selected economies. Extending the analysis to 2023–2025 would lead to a substantial loss of observations for some key variables and would reduce the balanced nature of the panel. The time frame also includes significant digital transformation and environmental policy shifts, such as the COVID-19 era and the fast-paced growth of digital technologies. Therefore, 2002–2022 provides a consistent period for cross-country comparison.

The final sample consists of 53 economies selected using data availability and panel completeness as the main criteria. Economies were included when consistent observations were available for the variables required to construct CEE and the main explanatory and control variables. To achieve a balanced panel, economies with a large number of missing observations were omitted. The final sample includes both developed and developing economies. This provides variation in digital development, ICTI, economic structure, IQI, and environmental performance. The sample thus enables the study to investigate whether the link between digitalization and CEE is different in different economies with different development conditions. Similarly, this diversity enables a more comprehensive evaluation of the digital paradox and mediating mechanisms in various economic and environmental settings. The functional representation of the SE-SBM model used in this study is shown below.

$$
\begin{aligned}
mini\ p &= \frac{1+\frac{1}{m}\sum_{i=1}^{m} s_i^- / x_{ik}}{1+\frac{1}{s}\sum_{r=1}^{s} s_r^+ / y_{rk}} \\
s.t. \sum\nolimits_{j=1,\ j\neq k}^{n} x_{ij}\gamma_j &- s_i^- \leq x_{ik} \\
\sum\nolimits_{j=1,\ j\neq k}^{n} y_{rj}\gamma_j &- s_r^+ \geq y_{rk} \\
&\begin{cases} \gamma, \quad s^-, s^+ \geq 0 \\ i = 1, 2, \ldots, m, \\ r = 1, 2, , \ldots, q, \\ j = 1, 2, \ldots n\ (j \neq k). \end{cases}
\end{aligned}
$$

In the SE-SBM model, *p* represents the efficiency score. The vector x represents the inputs, including labor, capital, and energy. The vector y represents the desirable output (GDP), while the undesirable output represents CO_2 emission. Both m and n denote the number of inputs and desirable outputs, respectively. Both and represent the excess use of inputs and the excess production of undesirable outputs, respectively. The weight vector (j) reflects the relative importance of the decision-making units to the reference technology. Moreover, i, k, and r show the input, output decision unit, and production period, respectively.

The first independent variable is digital infrastructure (DII), which is built on several indicators that reflect various aspects of digital development. They are subscribers of mobile cellular, users of the Internet, subscribers of fixed broadband, and subscribers of fixed telephone. Together, these indicators characterize the extent of embedding digital technologies in economic systems, from the availability of infrastructure to the adoption of digital technology. Therefore, these indicators reflect access to and availability of digital communications infrastructure. Data for all are taken from the World Development Indicators (WDI). A high index value of DII indicates a wider DII and connectivity.

The second key variable is industrial structure (INDS) as reflected by the indicators of industrial contribution, manufacturing activity, and the composition of trade. These measures reflect the structure of economic activity and its production and trade orientation. INDS is closely related to energy use and emissions and is therefore relevant in the context of inter-country differences in CEE.

ICTI captures the economic scale and structural importance of ICT-related activities. It differs from DII, which primarily focuses on digital infrastructure and connectivity. ICTI is constructed from ICT goods exports, ICT goods imports, and ICT service exports. ICT goods exports reflect the international supply of ICT products. ICT goods imports reflect the external supply of ICT hardware and related technology. ICT service exports include international activity in ICT-related services, including software, telecommunications, information services, and digital business services. These indicators reflect the trade and service aspects of the economic activity of using ICT. Because they have different units and levels of variation, the entropy method is used to construct the composite ICTI. A higher ICTI signifies more involvement in ICT activities of production, trade, and services. This distinction is important because wider DII may improve efficiency, while greater ICT-related economic activity may also increase energy and resource demand.

GI is defined as technological innovation to achieve resource efficiency, reduction in pollution, cleaner production, and environmental sustainability. For the study analysis, GI is proxied using resident patent applications, as similar data across countries and for green patents are not available on a consistent basis for the full 2002–2022 time series and 53 economies. Patent applications are an indicator of an economy's ability to create and safeguard new knowledge and technological innovation. While not every patent is exclusively environmental in nature, a robust innovation ecosystem and technological capacity will generally lead to a greater number of patents, which can help to develop and diffuse cleaner production technologies, energy-efficient technologies, and environmentally friendly solutions. Since patent applications measure the results of research and development initiatives and technological advancement, they have been acknowledged as a measure of innovation performance. However, total resident patent applications include both environmental and non-environmental patents. Therefore, this measure should not be interpreted as a direct measure of environmental patents. Thus, a measure of GI capacity is provided by resident patent applications, and this measure can be used to analyze the innovation channel on which digitalization can potentially have an impact on CEE.

Institutional quality (IQI) is a measure of how well governance systems, regulations, and public institutions promote economic and environmental performance. In this study, IQI is formed by six commonly used governance indicators from the Worldwide Governance Indicators (WGI) database, including political stability and absence of violence (PV), voice and accountability (VA), rule of law (RL), regulatory quality (RQ), government effectiveness (GE), and control of corruption (CC). These indicators focus on the main aspects of institutional performance, such as public involvement in governance, political stability, quality of public services, capacity to develop and implement effective policies, compliance with legal frameworks, and fighting corrupt practices. Effective institutions enable policy implementation, increase compliance with the rules, encourage innovation, and contribute to better resource use efficiency, all of which contribute to better environmental outcomes and CEE.

The DII, ICTI, IQI, and INDS indices were calculated using the entropy method. Variability in the data was used to assign weights to these indicators by applying the entropy method, which provides an objective aggregation method. The entropy method assigns greater weights to indicators with greater information variation and reduces subjective weighting by the researcher. Therefore, the entropy method was suitable for constructing these indices. Unlike subjective weighting methods, entropy weights are calculated based on the level of data dispersion, which reduces researcher bias. The entropy method does not require any correlation structure among the indicators, unlike the principal component analysis (PCA) method, to reduce the information structure and enhance the interpretability. When variables have different units and economies are heterogeneous, the entropy method is particularly appropriate. This approach is useful, particularly when indicators are measured in different units, and economies show different degrees of variation.

In addition to DII, ICTI, and GI, this study considers INDS, IQI, and economic growth (GDP) as control variables. ICTI, DII, GI, INDS, IQI, and economic growth (GDP) analyses were controlled. INDS captures differences in the composition of economic activities. IQI captures the role of governance and policy capacity. GDP controls for differences in economic development. The squared GDP term was included separately to test the Environmental Kuznets Curve (EKC) relationship. The variable descriptions and data sources are provided in Table 2. The square of GDP was also included in the model to analyze the hypothesis on the Environmental Kuznets Curve (EKC).

The baseline model was developed in Equation (1) including all the dependent and independent variables:

$$\text{CEE} = \text{f}(\text{DII, INDS, INQ, GDP}) \quad (1)$$

To analyze the EKC hypothesis in terms of CEE, the baseline model in Equation (1) was modified by including the square form of GDP as presented in Equation (2).

$$\text{CEE} = \text{f}(\text{DII, INDS, INQ, GDP, GDP}^2) \quad (2)$$

The variable transformations were carefully considered to ensure comparability and minimize the potential for scale-related distortions. The GDP and GI are log-transformed because of the great size and high degree of cross-country variation in GDP and patents. Variables such as DII, INDS, ICTI, IQI, and CEE are not transformed because they are bounded range indices and are retained in their original form. Thus, these variables are not log-transformed to maintain these ranges and to be interpretable across countries. In this way, the meaning of the index values remains unchanged, and no unnecessary transformation is performed. The empirical baseline model is specified as follows:

$$CEE_{it} = \alpha_{it} + \beta_1 DII_{it} + \beta_2 INDS_{it} + \beta_3 IQI_{it} + \beta_4 lnGDP_{it} + \beta_5 lnGDP_{it}^2 + \in_{it} \quad (3)$$

where α_{it} and β's are the parameters to be measured. The cross-sectional unit is denoted by I, and t is the time period.

3.1. Mediation Model

To analyze the GI mediation, the base-line model was modified. At first, the dependent variable in Equation (3) was replaced with GI to determine the impact of DII on GI, and the following model was specified.

$$lnGI_{it} = \delta_{it} + \delta_1 DII_{it} + \delta_2 INDS_{it} + \delta_3 IQI_{it} + \delta_4 lnGDP_{it} + \delta_5 lnGDP_{it}^2 + \in_{it} \quad (4)$$

In the next step, GI was included with DII simultaneously in the baseline model, specified as given below in Equation (5).

$$CEE_{it} = \gamma_{it} + \gamma_1 DII_{it} + \gamma_2 lnGI_{it} + \gamma_3 INDS_{it} + \gamma_4 IQI_{it} + \gamma_5 lnGDP_{it} + \gamma_6 lnGDP_{it}^2 + \in_{it} \quad (5)$$

The mediating role of GI was examined using three relationships. First, GI was regressed on the DII to estimate the effect of digitalization on GI. Second, CEE was regressed on DII to estimate the total effect. Third, CEE was regressed on both DII and GI to estimate the direct effect of digitalization and GI.

The indirect effect was $\delta_1 \times \gamma_2$, where δ_1 is the effect of DII on GI and γ_2 is the effect of GI on CEE after adjusting for DII. The direct effect was represented by γ_1, which indicates the effect of DII on CEE while GI is controlled, whereas the total effect was represented by β_1. The proportion mediated was calculated as $(\delta_1 \times \gamma_2)/c$. Moreover, a Sobel test and a bootstrap test were employed to evaluate the statistical significance of the indirect effect. The mediation results therefore report the direct, indirect, and total effects and the proportion of the total effect transmitted through GI.

Table 2. Independent variables, their sources and description.

Variables	Description of Indicators	Units	Variable Role	Source
Digital infrastructure index (DII)	Subscribers to fixed telephone	Per 100 people	Main IDV	WDI
	Subscribers to mobile cellular			
	Subscribers to fixed broadband			
	Users of the Internet	% of population		
ICT Intensity (ICTI)	ICT goods export	% of total goods export	Moderator	
	ICT goods import	% of total goods import		
	ICT service exports	current US$		
Green Innovation (GI)	Residents patent applications	Numbers	Mediator	
Industrial Structure (INDS)	Industrial value added	% of GDP	Control	
	Manufacturing value added	% of GDP		
	Trade intensity	Export and import (% of GDP)		
GDP	Gross domestic product	Current US$		
Institutional quality (IQI)	Measured from Political Stability and Absence of Violence (PV), Voice and Accountability (VA), Rule of Law (RL), Regulatory Quality (RQ), Government Effectiveness (GE), and Control of Corruption (CC).	Score		WGI

Note: WDI = World Development Indicators; WGI = World Governance Indicators.

3.2. Digital Paradox

The digital paradox is examined by modifying the baseline model, including ICTI, to determine the impact of both DII and ICTI in the presence of control variables, and the following model was specified as in Equation (6).

$$CEE_{it} = \alpha_{it} + \beta_1 DII_{it} + \beta_2 ICTI_{it} + \beta_3 INDS_{it} + \beta_4 IQI_{it} + \beta_5 lnGDP_{it} + \beta_6 lnGDP_{it}^2 + \in_{it} \quad (6)$$

Further, the interaction term (DII X ICTI) was included in the model, and the following Equation (7) was specified. This will identify whether ICTI strengthens or weakens the effect of DII on CEE.

$$CEE_{it} = \alpha_{it} + \beta_1 DII_{it} + \beta_2 ICTI_{it} + \beta_3 DII \times ICTI_{it} + \beta_4 INDS_{it} + \beta_5 IQI_{it} + \beta_6 lnGDP_{it} + \beta_7 lnGDP_{it}^2 + \in_{it} \quad (7)$$

Therefore, the DII coefficient represents the effect of digitalization when ICTI equals zero. This should not be interpreted as the overall effect of the DII at all levels of the ICTI. To provide a clearer interpretation, the marginal effect of the DII was calculated at the 25th, 50th, and 75th percentiles of the ICTI. A marginal-effects plot is also used to show how the effect of the DII changes as ICTI increases.

The econometric analysis begins with a test for cross-sectional dependence. Economies across the region can be impacted by shared global events, trade ties, financial ties, and policy spillovers. Ignoring such dependence may lead to incorrect statistical inference. Therefore, the Breusch-Pagan LM test [48] and Pesaran CD test [49] are applied. The results are then used to inform the selection of the next panel estimation and unit-root procedures. The functional forms of the LM- and CD-tests are presented in Equations (8) and (9), respectively.

$$LM = T\sum_{i=0}^{N-1}\sum_{j=i+1}^{N-1}\hat{p}_{ij}^2 \quad (8)$$

$$CD = \sqrt{\frac{2T}{N(N-1)}}\sum_{i=0}^{N-1}\sum_{j=i+1}^{N-1}\hat{p}_{ij}^2 \quad (9)$$

where T indicates the time period, N is the total number of countries in the panel, and $\hat{p}_{ij}^2$ is the residual cross-sectional correlation between i and j nations.

After testing for cross-sectional dependence, the cross-sectionally augmented Dickey–Fuller (CADF) and cross-sectionally augmented IPS (CIPS) [50] are applied. These tests incorporate cross-sectional averages into the unit-root process, thereby accounting for cross-sectional dependence. The tests are used to determine whether the variables are stationary in levels or become stationary after first differencing. Moreover, in the presence of heterogeneity, both CADF and CIPS provide robust results [51]. This information is important for selecting an appropriate long-run estimation strategy. Equation (10) indicates the general functional form of CADF.

$$\Delta X_{it} = \delta_i + \theta_i X_{it-1} + \theta_i \bar{X}_{it-1} + \sum_{i=0}^{p}\theta_{it}\Delta\bar{X}_{it-1} + \sum_{i=0}^{p}\vartheta_{it}\Delta X_{it-1} + \varepsilon_{it} \quad (10)$$

where

$\bar{X}_{it-1}$ = Cross-sectional average for the lag of each series of variables.

$\Delta\bar{X}_{it-1}$ = Cross-sectional average of the first difference in each series.

Further, CIPS was obtained by using CADF in Equation (11) as follows:

$$CIPS = \frac{1}{N}\sum_{i=1}^{n} CADF \quad (11)$$

Subsequently, it was necessary to ensure that the independent variables were cointegrated in the long run. Hence, the no cointegration null hypothesis was tested using the statistics proposed by Westerlund and Edgerton [52]. The two statistics are one for groups

(Ga, Gt) and one for panels (Pt, Pa). The important result indicates that the null hypothesis was rejected, and that long-term cointegration exists.

$$\Delta Y_t = \delta_i d_t + \omega_i Y_{i,t-1} + \acute{\gamma}_i X_{i,t-1} + \sum_{j=1}^{pi} \omega_{ij} \Delta Y_{i,t-1} + \sum_{j=-qi}^{pi} \gamma_{ij} X_{i,t-1} + \mu_{it} \quad (12)$$

where

Y = Dependent variable.
X = Independent variable.
dt = A probable factor with a constant trend.
i = Cross-sectional units.
t = Time period (2002–2022).
ωi = Error correction term indicating the speed of adjustment toward long-run equilibrium.
In addition, the following equations describe Gt, Ga, Pt and Pa:

$$G_t = \frac{1}{K} \sum_{i=1}^{K} \frac{b_i}{SE(b_i)} \quad (13)$$

$$G_a = \frac{1}{K} \sum_{i=1}^{K} \frac{Tb_i}{b_i(1)} \quad (14)$$

$$P_t = \frac{b_i}{SE(b_i)} \quad (15)$$

$$P_a = Tb_i \quad (16)$$

For robustness, the KAO and Pedroni cointegration tests were also performed. The strength of the cointegration analysis was increased by using the following tests simultaneously: the Westerlund, Kao, and Pedroni tests. The simultaneous use of these three cointegration tests increases the strength of the cointegration analysis as it combines the error-correction-based and residual-based approaches while using cross-sectional heterogeneity and long-run equilibrium dynamics.

The cointegration results indicate the presence of a long-run relationship among the variables. The variables are stationary and first-difference stationary; thus, the estimation method was chosen considering the panel structure and cross-sectional dependence. The baseline estimation was performed using PCSE as the central aim was to obtain sound inferences while controlling for heteroscedasticity and contemporaneous correlation across economies. Moreover, the Pooled Mean Group (PMG) estimator was used as a robustness check for the long-run relationship. Comparing the PMG results with the baseline results provides additional evidence on the stability of the estimated relationships.

The main estimator is panel-corrected standard errors (PCSE) following Beck and Katz [53]. PCSE is suitable for panels that could be heteroscedastic and have contemporaneous correlation between cross-sectional units. It enhances statistical inference if shocks in one economy can be conditionally related to shocks in another economy. The baseline estimator is PCSE, and the alternative estimators are used to test the robustness of the findings.

System-GMM was used as an additional estimator to address potential dynamic endogeneity and the persistence of CEE. In particular, the lagged dependent variable was treated using GMM-style internal instruments based on its lagged values. This method can be used to account for the time-varying nature of CEE and to mitigate the potential bias created by the inclusion of the lagged dependent variable. The model also includes digitalization, INDS, GDP, GDP squared, ICTI, IQI, and year effects. The endogeneity of the DII and CEE relationship is also acknowledged. Reverse causality may exist because economies with different levels of CEE may adopt digital technologies differently, while digitalization may also affect CEE. However, the present study does not include an additional exogenous instrumental variable for DII. Therefore, the System-GMM results are interpreted as additional robustness evidence rather than as proof that all possible endogeneity has been

eliminated. The validity of the System-GMM specification was assessed using the Hansen test and the Arellano–Bond serial-correlation tests. The GMM instruments were collapsed to limit the number of instruments and reduce the risk of instrument proliferation. These procedures provide additional evidence on the robustness of the main findings, while the possibility of remaining endogeneity is acknowledged.

Driscoll and Kraay's [54] robust standard error (DKSE) is also used as a robustness estimator. In the case of cross-sectional dependency, DKSE regression also offers good outcomes. Additionally, in the presence of heteroscedasticity, cross-sectional dependency, and autocorrelation, DKSE provides robust estimates [55]. DKSE is also used as a robustness estimator. It can be used for panel data models where serial correlation, cross-sectional dependence, and heteroscedasticity are present. When the variables are cointegrated, the evidence on the long-run relationship will be obtained from PMG, whereas when the variables are dynamically endogenous, an additional check will come from System-GMM. Therefore, PCSE, System GMM, and DKSE are valid for dealing with heteroscedasticity, cross-sectional dependency, and scale differences. These methods do not require variables to be measured on the same scale. The interpretation is based on the consistency and significance of the parameters rather than the magnitude of the variables.

4. Results and Discussion

4.1. Descriptive Statistics

The descriptive statistics of the study variables are presented in Table 3. The mean CEE value is 0.6946, indicating that the average CEE is approximately 69.46% of the optimal frontier. However, there are clear variations in the minimum and maximum values among the sampled economies. The mean values of DII (0.4775) and ICTI (0.1169) also show differences in digital development. The average value of the GI is 3.0093 with a standard deviation of 1.1058, showing that the amount of innovation activity measured varies across the sample economies. The variation is included because it helps to provide descriptive context for investigating how GI can act as a potential mediating variable between DII and CEE. These variations provide a useful basis for examining whether DII has different environmental effects across economies. The wide range of INDS, IQI, and GI further indicates differences in INDS, IQI, and GI. These differences may help explain variations in CEE. The skewness and kurtosis statistics indicate that the distributions of ICTI and INDS are more asymmetric than those of the other variables. The Jarque–Bera test also rejects normality for most variables. These results suggest that the variables differ in their distributional characteristics.

Table 3. Descriptive analysis.

Parameters	CEE	DII	ICTI	INDS	IQI	lnGDP	GI
Mean	0.6946	0.4775	0.1169	0.0213	0.5616	11.4401	3.0093
Standard Deviation	0.1904	0.2098	0.1036	0.3047	0.2347	0.7644	1.1058
Minimum	0.2913	0.0037	0.0021	−0.5911	0.1031	9.2206	0.3010
Maximum	1.0000	0.8549	0.6228	1.6695	0.9809	13.4083	6.1543
Skewness	0.2336	−0.4386	1.6911	2.0944	0.0615	−0.0532	0.3055
Kurtosis	1.7728	2.1314	6.1036	9.3215	1.6883	2.7534	3.1815
JB-test	79.96 *	70.67 *	977.20 *	2667.01 *	80.49 *	3.344	8.84 *

CEE = carbon emission efficiency, DII = digital infrastructure index, ICTI = ICT index, INDS = industrial structure, IQI = institutional quality, GI = green innovation, * shows significance level at 1%.

4.2. Cross-Sectional Dependence Test

The results of the BP-LM and Pesaran CD tests in Table 4 indicate that all variables, CEE, DII, ICTI, INDS, IQI, lnGDP, and GI are highly significant ($p < 0.001$). Thus, the results of the tests reject the null hypothesis of cross-sectional independence for all variables. This provides evidence of a robust cross-sectional dependence between countries. The findings indicate that the sampled economies are highly interdependent through trade linkages, digital diffusion, and environmental policy transmission. The results support the use of estimation and testing procedures that account for cross-sectional dependence when examining the relationship between digitalization and CEE.

Table 4. Cross-sectional dependency test.

Parameters	BP-LM Test		Pesaran-CD Test	
	Score	*p*-Value	Score	*p*-Value
CEE	10,641.264	0.000	58.708	0.000
DII	25,896.820	0.000	160.611	0.000
ICTI	7478.040	0.000	16.900	0.000
INDS	13,306.183	0.000	72.831	0.000
IQI	8581.498	0.000	15.42	0.000
lnGDP	21,895.625	0.000	144.560	0.000
GI	8337.338	0.000	3.497	0.000

CEE = carbon emission efficiency, DII = Digital infrastructure index, ICTI = ICT index, INDS = Industrial structure, IQI = institutional quality, GI = Green innovation.

4.3. Unit Root Tests

The results of the CIPS and CADF panel unit root tests are presented in Table 5. The results indicate that the stationarity properties differ across the variables and tests. Several variables fail to reject the unit-root null hypothesis at the level but become stationary after the first differencing. These results show that most of the variables are non-stationary at level but stationary after first differencing, which suggests that all variables are of integrated order one, I(1).

Table 5. Unit root analysis.

Parameters	CIPS		CADF	
	At Level	1st Difference	At Level	1st Difference
CEE	−2.118 **	−4.311 *	−1.733	−2.206 *
DII	−2.429 *	−3.681 *	−2.179 *	−2.326 *
ICTI	−1.800	−3.790 *	−1.872	−2.348 *
INDS	−2.285 *	−3.720 *	−1.764	−2.087 *
IQI	−1.572	−4.066 *	−1.165	−2.197 *
lnGDP	−2.590 *	−3.534 *	−1.930 ***	−2.150 *
GI	−2.842 **	−4.790 *	−2.000 **	−2.642 *

CEE = carbon emission efficiency, DII = Digital infrastructure index, ICTI = ICT index, INDS = Industrial structure, IQI = institutional quality, GI = Green innovation. Note: *, and **, *** indicates significance at 1%, and 5%, respectively.

4.4. Panel Cointegration Tests

The results of the Westerlund, Kao, and Pedroni panel cointegration tests are presented in Table 6. The Westerlund Gt and Pt statistics show that the null hypothesis of no cointegration is rejected at the 1% level. The Ga and Pa statistics were not significant. Kao and Pedroni's results also provide evidence of cointegration through several significant test statistics. Overall, the results support the existence of a long-run relationship among the study variables, although the evidence varies across the individual tests.

Table 6. Panel cointegration test.

Westerlund test				
Statistic	Gt	Ga	Pt	Pa
Value	−2.473	−4.080	−11.635	−3.435
Z-value	−3.747	10.630	−6.616	7.993
Robust *p*-value	0.006	0.474	0.004	0.580
Kao test	Statistics		*p*-value	
Modified Dickey–Fuller t	−2.2607		0.0119	
Dickey–Fuller t	−3.0796		0.0010	
Augmented Dickey–Fuller t	−3.3910		0.0003	
Unadjusted modified Dickey–Fuller t	−3.8309		0.0001	
Unadjusted Dickey–Fuller t	−3.9203		0.0000	
Pedroni test				
Modified Phillips–Perron t	8.5395		0	
Phillips–Perron t	−2.166		0.0152	
Augmented Dickey–Fuller t	−2.4179		0.0078	

The presence of cointegration provides grounds for studying the long-run relationships between the DII, GI, and CEE. This also indicates that the variables can be analyzed within a long-run framework. However, cointegration alone does not establish the existence of a digital paradox or mediation effect. These possibilities must be evaluated using the regression and mediation results presented in the next sections.

4.5. Digitalization and Carbon Emission Efficiency

Table 7 presents the baseline results using the PCSE estimator to examine the impact of variables on CEE. Overall, the model is statistically robust, as indicated by the Wald chi-square value ($2357.61, p < 0.01$) and R^2 of 0.3086, showing that the explanatory variables jointly explain a meaningful proportion of the variation in CEE.

The results show that DII negatively and statistically significantly affects CEE ($\beta = -0.1677, p < 0.01$). This indicates that digitalization is correlated with a reduction in CEE. This reinforces the existence of a digital paradox, in which the initial phase of digitalization drives up energy use and the carbon-intensive use of energy (such as in data centers and ICT infrastructure), reducing efficiency gains. This finding is in line with prior studies that analyze the environmental costs of rapid digital expansion during the early stages of digital transformation. DII development has been shown to increase electricity consumption through data centers, cloud computing facilities, and communication networks. This generates additional carbon emissions before efficiency gains materialize. This finding is consistent with Peng and Qin [56], who found that digitalization increases

electricity rebound effects, and Peng et al. [57], who reported a 7–20% increase in electricity consumption across Chinese cities due to digital development. Similarly, Liu et al. [58] found that digital technology innovation reduces carbon emissions but also triggers an energy rebound effect that partially offsets these gains. Together, these studies support the finding that digitalization can increase energy demand and weaken CEE, despite its potential environmental benefits.

Table 7. Baseline Model (PCSE).

Variables	Coefficient	Standard Error
DII	−0.1677 *	0.0292
INDS	−0.0598 *	0.0078
IQI	0.4047 *	0.0224
LnGDP	−0.7859 *	0.0202
LnGDP2	0.0153 *	0.0004
Constant	10.6045 *	0.2720

Dependent Variable = CEE: R-squared = 0.3086; Wald chi2(5) = 2357.61: Prob > chi2 = 0. Note: *, indicate significance at 1%.

A negative and significant effect is also found for INDS ($\beta = -0.0598$), which indicates that a more resource-intensive or less advanced structure of industries negatively affects the CEE. The negative impact of INDS supports the argument that countries with resource- and pollution-intensive industries face bigger challenges in improving environmental efficiency. Anzolin and Lebdioui [59] stressed the need for green industrial policy and low-carbon innovation for sustainable industrial transformation. Similarly, Lu et al. [60] found that industrial upgrading can improve energy efficiency and promote cleaner energy use, although technological complexity may initially slow this process. These studies support our finding that INDS is an important factor in CEE. They stated that industrial upgrading and the transition toward knowledge-intensive sectors are essential for improving carbon efficiency and achieving sustainable development goals.

Conversely, IQI has a strong positive effect ($\beta = 0.4047$), signifying that good governance, regulatory oversight, and institutional capabilities are important for enhancing environmental performance through compliance and facilitating the implementation of green policies. This result aligns with the growing body of literature emphasizing the role of IQI in environmental sustainability. Azimi et al. [61] and Limei et al. [62] found that countries with higher governance quality are better positioned to translate technological progress into environmental gains.

The results also indicate a non-linear relationship between economic growth and CEE, with a negative coefficient of lnGDP ($\beta = -0.7859$) and a positive coefficient of lnGDP^2 ($\beta = 0.0153$). This suggests that the relationship between economic growth and CEE is a U-shaped Environmental Kuznets Curve (EKC), meaning that economic growth has an impact that varies as economies mature. This means that in the early stages of growth, economic expansion reduces the CEE, while after a certain level of growth, the structural change and technological upgrading of the economy increase efficiency. This finding is consistent with that of Almugren et al. [4], who also found a U-shaped relationship between GDP and CEE. Moreover, Dahmani [63] confirmed an inverted U-shaped relationship between economic growth and greenhouse gas emissions in G7 countries. Similarly, Doğan et al. [64] found that green technology innovation and fiscal expenditure reduce carbon emissions, highlighting the role of technological progress and environmental policies in improving environmental performance. Although these studies examine environmental outcomes rather than CEE

directly, their findings provide related evidence on the changing relationship between economic growth and environmental performance.

The findings are partly consistent with the ecological modernization perspective, which links environmental improvement with technological progress, institutional capacity, and structural change. He et al. [65] and Guo et al. [66] also discuss the importance of governance, innovation, and green technologies in shaping the environmental effects of digitalization. However, the negative DII coefficient indicates that DII is associated with lower CEE in the baseline model.

4.6. Green Innovation as a Mediating Mechanism in the Digitalization-Carbon Emission Efficiency Nexus

Table 8 presents the mediation results regarding the role of GI in the relationship between DII and CEE. The results reveal that DII has a significant negative impact on GI ($\beta = -0.0820$, $p < 0.01$) in Model A, indicating that DII does not necessarily lead to a higher level of green innovative capacity. This may be due to the high energy demand and lack of environmental goals in digital expansion. This interpretation is consistent with Ding et al. [67] and Avom et al. [68]. The negative relationship between INDS and GI ($\beta = -0.4341$) suggests that the adoption of more resource-intensive industrial production systems limits the growth of GI [69,70]. However, the effect of IQI on GI is positive ($\beta = 0.2901$, $p < 0.05$), indicating that data on all three dimensions of IQI, such as governance quality, regulatory enforcement, and institutional stability, are important for promoting environmentally oriented innovation [71,72]. The variable lnGDP has a significant negative ($\beta = -4.3695$), whereas the variable $\ln GDP^2$ has a positive and significant relationship with GI ($\beta = 0.1061$), indicating an inverted U-shape. This suggests that GI is initially negatively related to growth at the lower levels of GDP but becomes increasingly positive as GDP increases and the average citizen's income level rises, allowing greater investment in clean technologies [73,74]. There is also a strong explanatory power for Model A ($R^2 = 0.78$), suggesting that the model can explain a significant amount of the variance in GI.

The findings of Model B indicate that GI has positive and statistically significant impacts on CEE ($\beta = 0.0089$, $p < 0.01$), which is consistent with the expectation that GI has positive effects on environmental performance by increasing resource efficiency, the use of cleaner production technologies, and decreasing the carbon intensity of the business [75,76]. Notably, the coefficient of DII is not only negative and significant ($\beta = -0.1669$) but also slightly smaller than in the baseline model; hence, the relationship between CEE and digitalization is partially mediated by GI. This implies that, on the one hand, the effects of digitalization on CEE decline (digital paradox), while, on the other, its influence is mediated via the effect on GI. The impact of IQI and economic growth is generally consistent with the baseline results. This finding aligns with Wang et al. [23], who found that IQI improved environmental quality in non-oil-producing African countries. Similarly, Mehmood et al. [77] reported that better IQI, including corruption control and the rule of law, promotes economic growth in South Asian countries. Makhdum et al. [78] also found that IQI reduces ecological footprints while supporting economic growth in China. These studies reinforce the critical role of effective institutions in enhancing environmental performance while promoting economic growth. Meanwhile, the positive and significant effect of GI suggests that it is an important channel through which digitalization can support CEE, although it only partially offsets the negative direct relationship between digitalization and CEE.

The mediation results showed that GI significantly mediated the relationship between DII and CEE; however, the mediation effect was very small. Table 9 indicates that DII had a negative effect on CEE (-0.1677) and also negatively affected GI (-0.0820), whereas GI had a small positive effect on CEE (0.0089). The resulting indirect effect of GI was -0.00073. The

Sobel test ($z = -3.19$) and bootstrap confidence interval supported a statistically significant indirect effect. However, the mediated proportion was only 0.44%, and the direct effect remained almost unchanged. Therefore, the GI explains only a small part of the negative association between the DII and CEE. The results support partial statistical mediation but do not show that GI resolves the digital paradox.

Table 8. Green innovation mediation.

Variables	Coefficient	Standard Error
Model A: Dependent variable = GI		
DII	−0.0820 *	0.0232
INDS	−0.4341 *	0.1188
IQI	0.2901 **	0.1443
LnGDP	−4.3695 *	0.3204
LnGDP2	0.1061 *	0.0058
Constant	47.9564 *	4.4394
R-squared = 0.78: Wald chi2(5) = 76,660.88: Prob > chi2 = 0.00		
Variables	**Coefficient**	**Standard error**
Model B: Dependent variable = CEE		
GI	0.0089 *	0.0023
DII	−0.1669 *	0.0262
INDS	−0.0560 *	0.0081
IQI	0.4022 *	0.0212
LnGDP	−0.7472 *	0.0216
LnGDP2	0.0143 *	0.0004
Constant	10.1800 *	0.2764
R-squared = 0.3117: Wald chi2(6) = 2799.08: Prob > chi2 = 0		

Note: *, **, indicate significance at 1%, 5%.

Table 9. Mediation effect of GI between the relations of DII and CEE.

Effect	Path	Score
Total effect = β_1	DII → CEE	−0.1677
Effect of DII on GI δ_1	DII → GI	−0.0820
Effect of GI on CEE γ_2	GI → CEE	0.0089
Direct effect	DII → CEE, controlling GI	−0.1669
Indirect effect ($\delta_1 \times \gamma_2$)		(-0.0820×0.0089)
Proportion Mediated	($\delta_1 \times \gamma_2$)/ β_1	0.44%

Note: Sobel-z value = −3.19.

4.7. Digital Paradox and Interaction Effects of Digitalization on Carbon Emission Efficiency

Table 10 presents an analysis of the direct and interactive impacts of DII and ICTI on CEE. The coefficients of both DII ($\beta = -0.2024$, $p < 0.01$) and ICTI ($\beta = -0.2724$, $p < 0.01$) are negative and significant in Model C. When estimating without the interaction term, both DII and ICTI are found to have a negative effect on the CEE. The results confirm that digital expansion leads to higher electricity consumption, more data processing, and more emissions related to infrastructure; this triggers short-run environmental stress. Santarius

et al. [32], Jorgenson and Vu [79], and Lange et al. [80] discuss the energy demand and rebound effects that can accompany digital expansion. The present findings are consistent with this concern. However, the interaction model provides a more detailed test of whether the association between DII and CEE changes with ICTI.

Table 10. Digital Paradox Model.

Variables	Model C		Model D	
	Coefficient	**Standard Error**	**Coefficient**	**Standard Error**
DII	−0.2024 *	0.0263	−0.1244 *	0.0404
ICTI	−0.2724 *	0.0320	−0.0695 **	0.0335
DII x ICTI	–	–	−0.6864 *	0.1449
INDS	−0.0360 *	0.0085	−0.0293 *	0.0085
IQI	0.4336 *	0.0213	0.4303 *	0.0223
LnGDP	−0.8643 *	0.0269	−0.8848 *	0.0244
LnGDP2	0.0169 *	0.0005	0.0173 *	0.0005
Constant	11.5753 *	0.3513	11.8052 *	0.3235

Model C: R-squared = 0.325: Wald chi2(6) = 2177.70: Prob > chi2 = 0.000. Model D: R-squared = 0.331: Wald chi2(6) = 2853.12: Prob > chi2 = 0.000. Note: *, **, indicate significance at 1%, 5%.

However, the interaction term between DII and ICTI (DII x ICTI) was added to Model D to provide a more nuanced picture. The interaction between DII and ICTI was negative and significant ($\beta = -0.6864$, $p < 0.01$). This indicates that the link between DII and CEE becomes more negative as ICTI increases. This result extends the existing literature by highlighting that the environmental link of DII depends on ICTI. This implies that without efficient use of ICTs, DII growth could increase energy consumption and environmental pressure. Without proper integration, digital expansion can intensify energy demand and emissions and decrease CEE [81–83].

The findings confirm the existence of a digital paradox but also indicate the possibility of a positive impact of ICTI. However, the negative interaction effect draws attention to the fact that if DII development is not coordinated with the efficiency of using ICTs, digitalization can exacerbate environmental degradation.

The marginal effects show that DII is negatively associated with CEE at all three reported levels of ICTI. The estimated effects are −0.1570 at the 25th percentile, −0.1743 at the median, and −0.2373 at the 75th percentile (Table 11). The negative relationship gets stronger with an increase in ICTI. This is similar to the situation in Model D, where the interaction coefficient was negative. The results suggest that the environmental implications of DII depend partly on ICTI.

Table 11. Marginal Effects of DII on CEE at Different Levels of ICTI.

ICTI Level	Marginal Effect of DII
P25 = 0.04744	−0.1570
P50 = 0.07273	−0.1743
P75 = 0.16445	−0.2373

The downward trend is also apparent in Figure 1, suggesting a negative marginal effect of the DII when ICTI increases from P25 to P75. This visual pattern further reinforces the interaction results and the existence of a digital paradox in the study.

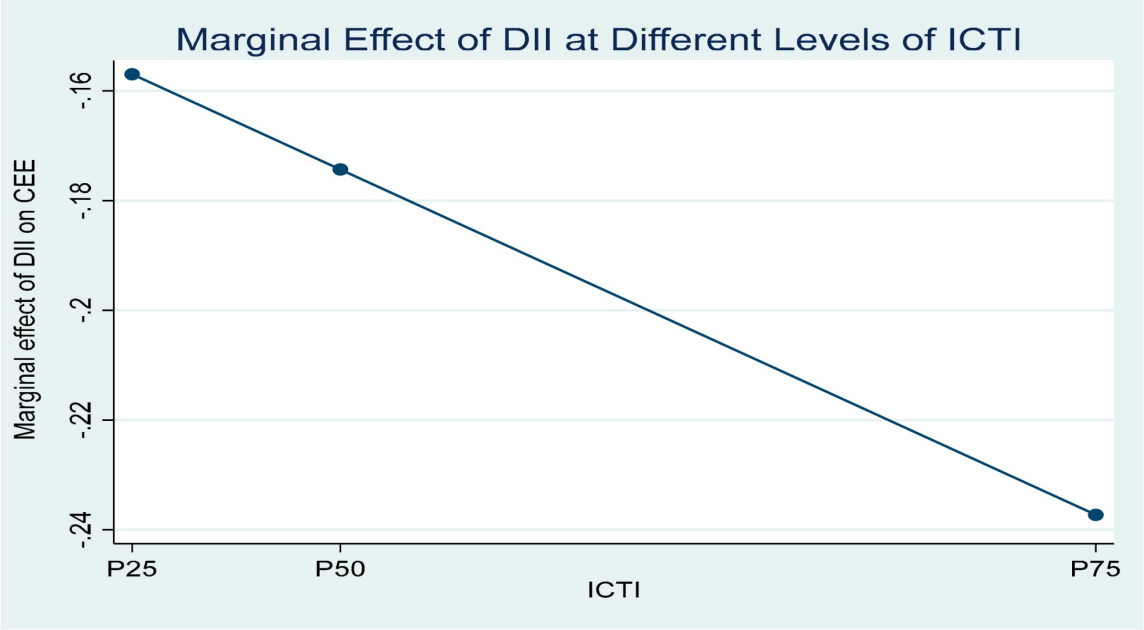


Figure 1. Plot of the marginal effect of DII on CEE at different levels of ICTI.

4.8. Robustness Tests

4.8.1. Robustness Analysis for Baseline Model (PCSE)

Table 12 contains robustness checks based on the System GMM, Driscoll-Kraay standard errors, and estimating the long-run PMG. The coefficient of DII is still negative and statistically significant in all three specifications. INDS also has a negative coefficient, while IQI has a positive coefficient. The negative coefficient of lnGDP and the positive coefficient of $lnGDP^2$ remain consistent with a U-shaped relationship between economic growth and CEE. Although the coefficient sizes differ across estimators, the main signs remain stable. The System GMM diagnostics do not indicate second-order serial correlation, and the reported Hansen and Sargan tests do not reject the instrument-validity restrictions. The overall results confirm the stability of the baseline results for alternative estimation methods.

Table 12. Robustness Analysis for Baseline Model (PCSE).

Variables	System GMM		DKSE		PMG-Long Run	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
L.CEE	0.8653 *	0.0319	–	–	–	–
DII	−0.1082 *	0.0171	−0.1677 *	0.0379	−0.1023 *	0.0192
INDS	−0.0156 *	0.0013	−0.0598 *	0.0095	−0.1927 *	0.0316
IQI	0.0440 *	0.0149	0.4047 *	0.0341	0.2686 *	0.0512
LnGDP	−0.2248 *	0.0623	−1.8096 *	0.0660	−0.4026 *	0.1331
LnGDP2	0.0102 *	0.0028	0.0810 *	0.0029	0.0560 *	0.0056
Constant	1.3018 *	0.3551	10.6045 *	0.3520	–	–
ECT	–	–	–	–	−0.3257 *	0.0379

System GMM: No. of instruments = 45. F-value = 17,161.90; Prob > Chi2 = 0.00. AR (2) = −1.62; *p*-value = 0.105. Sargan test score = 40.34; *p*-value = 0.571. Hansen test score = 23.74; *p*-value = 0.206. DKSE: F-value = 482.07; Prob = 0.000. R^2 = 0.2278. * show significance at 1%.

4.8.2. Robustness Analysis for Green Innovation Mediation

Table 13 confirms the robustness of the GI mediation results using PMG, System GMM, and DKSE. The coefficient of DII remains negative in the reported GI and CEE models. Diagnostic tests confirm model validity. In the CEE model, GI positively affects CEE, while DII remains negative and significant across both estimators. The findings strongly validate the stability of the mediation pathway, confirming that GI transmits the effect of DII on CEE and supports the digital paradox resolution mechanism.

Table 13. Robustness analysis for green innovation mediation.

Variables	System GMM		DKSE		PMG-Long Run	
	Coefficient	**Standard Error**	**Coefficient**	**Standard Error**	**Coefficient**	**Standard Error**
Model A-Robust: Dependent variable = GI						
L.GI	1.0013 *	0.0151	–	–	–	–
DII	−0.0756 *	0.0236	−0.0656 **	0.0251	−0.0327 *	0.0057
INDS	−0.0280 *	0.0051	−0.1885 *	0.0333	−0.1236 **	0.0575
IQI	0.1138 *	0.0138	0.1260 *	0.0145	0.8793 *	0.1464
LnGDP	−3.2667 *	0.6261	−1.3695 *	0.2163	−0.7747 *	0.0773
LnGDP2	0.1125 *	0.0281	0.2443 *	0.0088	0.2290 *	0.0331
Constant	1.4675 *	3.5020	20.8272 *	1.3894	–	–
ECT	–	–	–	–	−0.4315 *	0.0528
System GMM: F-value = 17,161.90; Prob > Chi2 = 0.00. AR (2) = −1.63 (0.104). Sargan test score = 33.28 (0.104); Hansen test score = 22.82 (0.245); No. of instruments (45) DKSE: F-value = 10,399.66; Prob = 0.000. R^2 = 0.5755						
Model B-Robust: Dependent variable = CEE						
L.CEE	0.8632 *	0.0310	–	–	–	–
GI	0.0095 ***	0.0050	0.0204 *	0.0033	0.0303 *	0.0017
DII	−0.1263 *	0.0208	−0.1669 *	0.0338	−0.1536 *	0.0211
INDS	−0.0547 *	0.0136	−0.0560 *	0.0100	−0.0528 *	0.0144
IQI	0.0550 *	0.0144	0.4022 *	0.0324	0.1925 *	0.0206
LnGDP	−0.1969 *	0.0715	−1.7205 *	0.0677	−0.1627 *	0.0116
LnGDP2	0.0085 **	0.0034	0.0760 *	0.0030	0.0372 *	0.0026
Constant	0.8632 *	0.0310	10.1800 *	0.3648	–	–
ECT	–	–	–	–	−0.3625 *	0.0163
System GMM: F-value = 17,408.73; Prob > Chi2 = 0.00. AR (2) = −1.73(0.105); Sargan test score = 18.27 (0.116). Hansen test score = 16.08 (0.652); No. of instruments (45) DKSE: F-value = 1563.46; Prob = 0.000. R^2 = 0.3117						

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

4.8.3. Robustness Check for Digital Paradox

The robustness results given in Table 14 through PMG, System GMM, and DKSE confirm the digital paradox. The negative coefficients of DII are consistent with the baseline results and suggest a negative impact of DII on CEE across the reported specifications. Similarly, the interaction coefficient remains negative, as in the baseline model. This means that the moderating role of ICTI is fully robust to the alternative specifications. The direct association between DII and CEE appears more stable than the interaction effect.

Table 14. Robustness check for digital paradoxINo issue.

Variables	System GMM		DKSE		PMG-Long Run	
	Coefficient	**Standard Error**	**Coefficient**	**Standard Error**	**Coefficient**	**Standard Error**
			Model C-Robustness			
L.CEE	0.9712 *	0.0564	–	–	–	–
DII	−0.3234 **	0.1262	−0.2024 *	0.0332	−0.2944 *	0.0372
ICTI	−0.2470 *	0.0468	−0.2724 *	0.0680	−0.2350 *	0.0524
INDS	−0.0619 **	0.0223	−0.0360 *	0.0116	−0.4139 *	0.0556
IQI	0.3329 *	0.1119	0.4336 *	0.0344	0.2299 *	0.0532
LnGDP	−0.2968 **	0.1211	−1.9901 *	0.1184	−1.7890 *	0.2065
LnGDP2	0.0180 *	0.0055	0.0895 *	0.0055	0.0698 *	0.0091
Constant	1.1071 *	0.7009	11.5753 *	0.6278	–	–
ECT	–	–	–	–	−0.2806 *	0.0390
System GMM: F-value = 6978.07; Prob > Chi2 = 0.00. AR (2) = −1.65 (0.19); Sargan test score = 30.18 (0.136); Hansen test score = 23.17 (0.184); Instrument numbers (45) DKSE: F-value = 1015.92; Prob = 0.000. R^2 = 0.3254						
Variables			Model D-Robust			
L.CEE	0.8757 *	0.0691	–	–	–	–
DII	−0.4035 **	0.1757	−0.2024 *	0.0332	−0.1897 *	0.0341
ICTI	−2.6606 *	0.7876	−0.2724 *	0.0680	−1.7651 *	0.3459
DII x ICTI	−0.6223 *	0.0346	−0.6267 *	0.0683	−2.9108 *	0.5418
INDS	−0.1541 **	0.0657	−0.0204 ***	0.0099	−0.2041 *	0.0350
IQI	0.3841 *	0.1122	0.4939 *	0.0333	0.6726 *	0.0859
LnGDP	−0.2273 **	0.0773	−1.9917 *	0.1036	−1.3225 *	0.4450
LnGDP2	0.0101 **	0.0024	0.0895 *	0.0048	0.1446 *	0.0197
Constant	1.4511 *	1.5537	11.5620 *	0.5454	–	–
ECT	–	–	–	–	−0.2970 *	0.0361
System GMM: F-value = 1881.26; Prob > Chi2 = 0.00; AR (2) = −1.56 (0.149); Sargan test score = 16.70 (0.519); Hansen test score = 17.71(0.408); Instrument numbers (45) DKSE: F-value = 1224.57; Prob = 0.000. R^2 = 0.3308						

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

5. Conclusions

This study examines the relationship between DII and CEE across 53 economies from 2002 to 2022. It focuses on digital infrastructure (DII) as the primary variable, ICT intensity (ICTI) as a moderator, green innovation (GI) as a mediator, and IQI, INDS, and economic growth as control variables. This study uses the SE-SBM model to measure CEE and applies several panel estimation techniques to examine the main relationships and check the robustness of the findings.

The results indicate that DII is negatively related to CEE. This finding supports the digital paradox, which suggests that the expansion of digital technologies does not always lead to better environmental performance. DII can provide a foundation for economic activity and technological advancements but can also result in energy consumption and the use of energy-intensive equipment. Therefore, expanding DII alone may not be sufficient to

improve environmental efficiency. The results also show that INDS is negatively associated with CEE, suggesting that economies with a greater presence of resource-intensive industrial activities may face more difficulty in improving carbon efficiency. In contrast, IQI is positively associated with CEE, highlighting the importance of effective governance and strong institutions in supporting environmental performance. The results also indicate a nonlinear relationship between economic growth and CEE, consistent with the findings of the environmental Kuznets curve.

The results of the mediation analysis indicate a positive relationship between GI and CEE and a negative relationship between DII and GI. However, the estimated indirect effect through GI accounts for only approximately 0.44% of the total effect. This implies that the pathway linking digitalization and CEE is statistically significant but small in terms of its magnitude. The findings thus indicate that innovation capacity could facilitate environmental performance, although the measured GI pathway only contributes a small proportion to the negative relationship between DII and CEE.

Moderation analysis provides further insight into the digital paradox. The interaction between DII and ICTI was negative and statistically significant in the baseline PCSE model. The marginal effect estimates also indicate that the negative relationship between DII and CEE is stronger at higher ICTI levels. These findings suggest that DII development and ICT-related activities may create environmental challenges when not supported by energy-efficient technologies and sustainable practices.

6. Policy Recommendations

Based on the findings of the study, there are many policy recommendations for achieving sustainability goals. First, DII policies should prioritize energy efficiency. Government policies should encourage energy-efficient data centers, communication networks, and digital equipment. They should also promote the use of renewable energy and establish environmental goals in the context of digital development. Second, policies should address the environmental impact of ICT-related activities. As DII and ICT-related economic activities may have different environmental effects, governments should promote cleaner electricity, energy-efficient equipment, and cleaner production in the ICT sector. Third, governments should strengthen support for GI. Governments should promote green research, development of clean technologies, and cooperation between universities and industries. These efforts can help ensure that digital progress contributes to environmental improvement. Fourth, stronger institutions and environmental regulations are needed. The positive relationship between INQ and CEE indicates the importance of good governance. Governments should enhance environmental regulation, enforcement, and transparency in environmental reporting. Enhanced coherence of digital, energy, industrial, and environmental policy can also help achieve sustainability objectives. Fifth, industrial policies should promote cleaner production. Therefore, governments should promote energy-efficient machinery, resource recycling, and low-carbon technologies. Industrial support should consider environmental performance alongside productivity and economic growth. Finally, governments should regularly assess the environmental impact of digital policies. Digital development should be evaluated not only through connectivity and investment but also through energy use, emissions, and environmental innovation. Through regular monitoring, policymakers will be able to detect issues and make necessary adjustments in their policy to promote sustainable digital and industrial development.

7. Study Limitations and Future Directions

This study also has several limitations. First, this study uses total resident patent applications as a proxy for green innovation (GI). However, these patents also cover tech-

nologies unrelated to environmental protection. Future studies should investigate using green patent data or other data that represent environmental innovation and note any significant differences in the results. The analysis is performed across 53 economies, but national data can hide industry and firm-level variations. Some industries can benefit from digitalization in terms of efficiency, while others consume more energy. Research needs to be conducted in the future at the firm level or industry level.

DII is an indicator of DII, and ICTI is an indicator of the economic activity related to ICT. However, these indicators do not adequately capture the production of digital hardware, the availability of data centers, and digital services production, nor their use in other sectors of the economy. Future studies should develop more detailed measures to identify which digital activities support environmental improvement and which increase environmental pressure.

This time span enables cross-economy comparisons but does not fully reflect the evolution of the CEE–digitalization relation over the various stages of digital development. The study also does not include 2023–2025 because there was no similar data for the selected sample. The findings could be expanded if appropriate data are available for a longer time period and should be compared to the findings in periods of technological change and environmental policy development in the future.

Although System-GMM mitigates some endogeneity issues, reverse causality and omitted variables may still influence the findings. For instance, digitalization can affect CEE, and environmental issues can spur additional digital investment. Other factors can also influence both variables, including energy policies and technology development. Better identification methods and proper instrumental variables (where available) should be employed in future studies. Hence, the estimated relationships should be viewed as approximate causal relationships.

Finally, this study does not directly assess the relative energy intensity of economies; instead, energy consumption is used as an input in the measurement of CEE. Future research could examine whether the relationship between digitalization and CEE differs across these groups. Further studies could also combine more precise GI measures, detailed digitalization indicators, and firm- or industry-level data. Such strategies would make it possible to better understand where digitalization can help improve the environment.

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