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Digital evolution and interaction of green initiatives with institutional instruments: emerging determinants of SDGs-2030 of BRICS

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Abstract
The study highlights the importance of sustainable development for achieving a sustainable environment, a pressing global issue. BRICS nations have adopted measures such as digitalization, green taxes, green energy, green innovation, and institutional reforms to improve environmental sustainability. For this purpose, this study employed a panel dataset covering 1990–2021. Panel cointegration, 3SLS, Newey West standard error regression, multivariate, mixed, and quantile regression were used to analyze the relationships between these factors, while FGLS, Drisc/Kraay, FMOLS, and DOLS were utilized to verify the robustness of the models. The empirical findings show that these factors positively impact environmental sustainability. Specifically, a 1% increase in the green index improves environmental quality by 1.861%, while a 1% increase in technology usage enhances it by 0.2867%. Additionally, a 1% improvement in institutional quality boosts sustainability by 0.1483%. However, a 1% increase in natural resource rents results in a 0.0505% decline in environmental quality, highlighting the detrimental effect of overexploitation. The study concludes that the key drivers of sustainable natural resource consumption and environmental protection in BRICS are digitalization, institutional quality, and green innovation. To achieve a sustainable environment, BRICS economies must strengthen institutional frameworks, promote green technology, regulate natural resource extraction, and pursue sustainable economic growth.

Keywords Digital economy · Environmental index · Green innovation · Institutional quality · 3SLS

1 Introduction

The digital economy can enable the more efficient use of resources, promote renewable energy, and reduce carbon emissions through telecommuting and virtual meetings. To ensure that the digital economy is sustainable, efforts should be made to promote responsible consumption and production of digital devices, encourage using renewable energy sources for digital infrastructure, and reduce energy consumption through

Extended author information available on the last page of the article efficiency measures. Moreover, the digital economy can enable greater access to information and education on sustainability, promoting awareness of and action toward environmental sustainability. The World Bank statistics indicate an 11.5 trillion USD digital economy in 2016, expected to surpass twenty-three trillion USD in 2025. Furthermore, the region's digital economy is projected to reach $2.88 trillion by 2025, with growth mainly driven by China, India, and Southeast Asia (Google et al., 2020). China is the world's major producer of e-waste, generating 10.1 million tons in 2019 (Global E-waste Statistics Partnership, 2020). The digital economy in North America is projected to grow 9.5% annually, reaching $4.2 trillion by 2025. Simultaneously, Europe has the world's most ambitious climate targets, intending to become climate-neutral by 2050. Therefore, many leading technology companies such as Abet (Google), SAP, and Siemens are expected to be part of this region. The European Union is taking steps to reduce the carbon footprint of the digital economy, including promoting energy-efficient data centers and supporting the development of renewable energy.

Environmental issues, climate change, smog, global warming, and contamination are of growing concern. The persistent burning of fossil and industrial fuels is one of these issues. As countries compete for resources, the demand for energy increases, leading to increased carbon emissions (Green, 2021). Therefore, environmental degradation is worsening globally, causing harm to life and property and demanding urgent action (Venmans et al., 2020). Experts advocate alternative energy sources, such as clean energy, to replace fossil fuels and achieve carbon neutrality. UN discussions on environmental issues are critical in this regard, and countries must make pledges and commitments, such as attaining net-zero carbon before 2050 at COP26 (Khan & Johansson, 2022).

Developing and emerging economies must implement significant actions to reduce CO_2 to meet the obligations of SDGs-2030 and COP27 commitments. However, this is not easy because economic growth should be maintained to improve living standards. Therefore, governments must elevate financial assistance to implement strategies, and lawmakers must promote development. Thus, active, sustainable environmental policy instruments can protect the environment and generate revenue (Liobikienė & Dagiliūtė, 2021). For example, Asian countries have adopted environmental trading systems (ETS), whereas Singapore and Japan impose carbon taxes (Song et al., 2021).

Considering global warming commitments regarding climate change mitigation reporting efforts, emerging economies often need help with public affairs. For example, China's initiatives to set aside 1.5 billion metric tons of CO_2 during 2005–2010 were considered the world's most significant national plan; however, China still needs to publicize it (Danish and Ulucak, 2020). Therefore, sustainable carbon neutrality is essential for sustainable development in China. Instead, emerging nations must focus on improving energy efficiency rather than adopting high-emission paths to combat global warming. It differs from the developed nations' approach of "pollution first, clean up later." Thus. The Chinese government considers carbon taxation and pricing for industries that are not participating in the emission trading market (Santra, 2017).

The ecological footprint is a critical measure of the environmental impact of human activities. It represents the amount of biologically productive land and water area required to produce the resources consumed and to absorb the waste generated by a population. This study considers the ecological footprint a key indicator of environmental sustainability, as it directly reflects economic activity pressure on the environment. In the context of BRICS nations, which are rapidly industrializing and urbanizing, the ecological footprint is an essential factor in assessing the sustainability of their growth. The study examines how digitalization and institutional quality influence the ecological footprint, aiming to identify strategies to reduce environmental degradation while supporting economic development.

Similarly, carbon emissions, primarily CO_2, are a major contributor to global climate change. They result from burning fossil fuels for energy, industrial processes, and transportation. This study includes carbon emissions as a central environmental factor, given their significant role in global warming and the urgent need to reduce them to meet international climate targets. The study focuses on how BRICS nations can reduce carbon emissions through digital innovations, green energy adoption, and improved institutional quality. The research aims to provide insights into effective policies for mitigating climate change while maintaining economic growth by analyzing the relationship between these variables and carbon emissions.

Studies have concluded that energy from renewable sources can slow the environmental decline and reduce carbon emissions (Stoll & Mehling, 2021). The use of green energy benefits economic and ecological development and reduces the dependence on fossil energy sources. Despite its growth, the use of renewable energy is limited by its high cost and technical limitations in some nations. Nevertheless, green technology can address environmental pollution significantly (Madaleno et al., 2022). It has been used to rejuvenate ecosystems and reduce carbon emissions while maximizing growth and minimizing ecological impacts. The implementation of these measures in cities is crucial. Encouraging carbon reduction and ecosystem absorption is also necessary for net-zero carbon emissions and environmental sustainability (Song et al., 2021).

The necessity of this study stems from the urgent need for emerging economies, particularly BRICS nations, to balance rapid economic growth with environmental sustainability, as these countries are major contributors to global carbon emissions and face significant challenges in achieving the Sustainable Development Goals (SDGs) by 2030. Despite the increasing adoption of digital technologies and green initiatives, there is a critical gap in understanding how these factors interact to impact environmental outcomes in these rapidly developing regions. Therefore, this study addresses this gap by providing empirical evidence on the effectiveness of digitalization, institutional quality, and green policies in promoting sustainable development in BRICS nations. Doing so offers actionable insights crucial for policymakers aiming to implement strategies harmonizing economic growth with environmental preservation.

The novelty of this research lies in its comprehensive approach to examining the intersection of digitalization, institutional quality, and green initiatives within the context of BRICS nations. For example, the study introduces a novel green index, which integrates green taxes, green energy, and green innovation, along with an institutional quality index. This combination allows for a more nuanced analysis of how these factors collectively influence environmental sustainability. Similarly, this research employs cutting-edge econometric techniques, such as 3SLS, quantile regression, FMOLS, and DOLS, to analyze panel data spanning over three decades. These methods provide robust and reliable insights into the long-term relationships between digitalization, institutional frameworks, and environmental outcomes. Finally, while much research has been conducted on environmental sustainability in developed economies, this study focuses on BRICS nations at the forefront of digital transformation and environmental challenges. This focus fills a significant gap in the literature by addressing these rapidly growing economies' unique dynamics and policy needs.

This study captures the association between environmental and institutional quality, sustainable economic growth, natural resources, the green index, and technological innovation. Thus, this study contributes to the literature in six ways. First, an environmental index incorporating the cumulative influence of carbon emissions and the ecological footprint was designed to assess environmental quality. Second, this study employed a green index based on green tax, green innovation, and green energy to measure their association with environmental quality and their role in achieving carbon neutrality. Third, technological innovations have drastically changed the world's face. This study develops a technological innovation index comprising fixed telephone subscribers, mobile cellular subscribers, and high-technology exports to capture the association of technological innovation with environmental quality to assess zero carbon. Fourth, to recognize the influence of institutional quality, this study employed government effectiveness and political stability with no violence to reduce carbon emissions in the economy. Fifth, the study used an exciting interaction term comprising the green and institutional quality index to recognize the influence on environmental quality to attain zero carbon in BRICS economies, considered the most prominent in carbon emissions. Finally, the study incorporates the latest dataset and modern econometric methods to measure the influence of quantiles and obtain fresh perspectives.

Thus, current research is essential for those engaged in academic and practical efforts to promote sustainability in the context of rapid digital and economic development. For scholars, this research contributes to the growing body of knowledge on how digitalization and green initiatives can influence environmental outcomes in emerging economies. The findings enhance theoretical understanding and provide a robust empirical foundation for future research in environmental economics, digital transformation, and sustainable development. For practitioners, particularly policymakers and environmental strategists, this work offers practical insights into how digital technologies and institutional frameworks can be leveraged to reduce ecological footprints and carbon emissions. By understanding the dynamics presented, practitioners can better design and implement strategies that promote sustainable natural resource consumption, foster green innovation, and enhance institutional quality to meet the Sustainable Development Goals (SDGs) by 2030.

The environmental degradation trend (see Fig. 1), consisting of environmental parameters (index of EFP and CO_2), shows similar patterns for Russia, China, India, and South

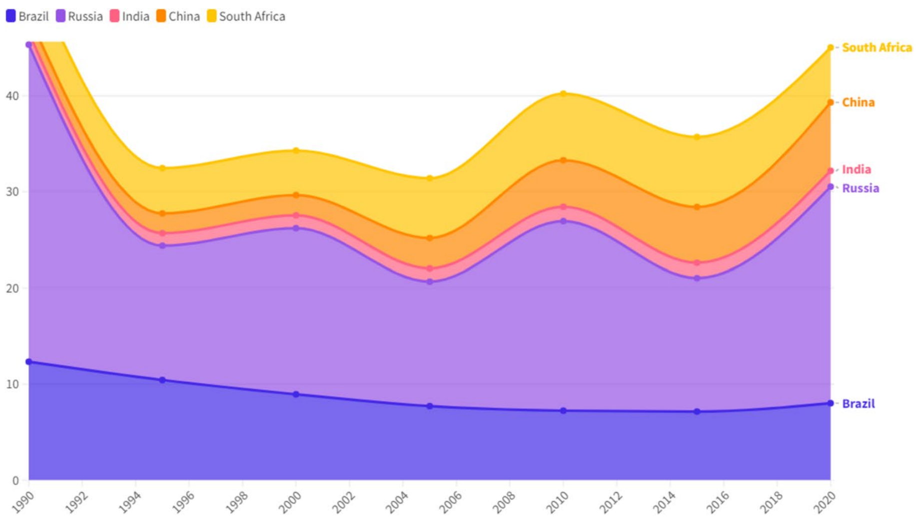

Fig. 1 Environmental quality for BRICS countries

Africa as decline starting from 1990 until 1995, reaching the lowest rates in 2005; beginning in 2005, there was a rise in environmental index parameters reaching the top in 2010, which can be related to the 2007 financial crisis and decline in the overall output production leasing to positive outcomes for the environment and another positive trend for the environment relating to the start of covid 19, however in Brazil, the trend of the environmental index represents a unique pattern.

2 Review of Literature

Numerous scholars have utilized a variety of factors and econometric approaches to investigate how to achieve zero carbon or lower carbon emissions in developed and developing economies to attain environmental sustainability. This section presents the relevant literature for formulating a hypothesis. Due to global warming, climate studies have gained significance in the past decade (Khudyakova & Urumov, 2021). Recent studies have utilized ecological footprints as a more precise parameter to assess environmental quality; therefore, it has gained popularity among researchers. For example, Luo et al. (2020) used it to evaluate global tourism and digital economy relations and concluded that energy sources of transportation and accommodation contribute eight percent to the worldwide increase of ecological footprints.

2.1 Digitalization and Sustainable Development

Furthermore, the growth of the digital economy has been considered a suitable replacement for physical appearances such as traveling for booking. Santarius et al. (2020) attempted to assess the impact of digitalization on climate change and energy consumption. This study also confirmed that digitalization's positive contribution is reducing ecological footprints and creating a sustainable environment. However, the production of digital devices and waste can negatively contribute to environmental sustainability. Anthony (2019) further discusses this concept, considering the CSR responsibilities of the ICT industry. This study demonstrates that green ICT strategies must be adopted for energy efficiency, sustainable development, environmental sustainability, and climate friendliness. According to this study, there is a need to improve the understanding of the development and utilization of digitalization. The same concept was used by De Dutta and Prasad (2020), who found that the Internet's carbon footprint is significant, with data centres and telecommunications networks being major contributors.

Further investigations reveal that environmental footprint affects both high- and low-middle-income economies. Various studies have analyzed the theoretical and empirical linkages between renewable energy, finance, urbanization, and GDP (Deng & Huang, 2020). The current research expands the scope to include factors such as the effectiveness of governance and communication technologies. The governance factor was introduced because it influences a country's GDP and encompasses government, institutions, and business entities.

2.2 Institutional Quality and Environmental Governance

Studies have shown that political stability and governance can positively affect climate change and CO_2 emissions. For example, research from 1990 to 2020 found that political stability increases ecological worth in South Asian countries and BRICS economies, and governance is environmentally sustainable in the MENA region (Korkut Pata et al., 2022). Sohail et al. (2022) showed that political stability improves climate change conditions, whereas democracy has a positive impact. However, this changed when the effects on ecological quality were assessed. RE projects can enhance environmental governance by providing collaborative structures. Although some studies have found that RE usage lowers carbon emissions, it can also increase production, and its impact on environmental pollution varies across countries (Mehmood, 2021).

The effectiveness of climate strategy is strongly linked to good governance and digital technology in promoting government transparency and improving policy implementation (Su et al., 2021). However, the impact of ICT on the environment can be very significant, as it contributes to 2% of human-generated carbon emissions from carriage and economic activities (Ulucak et al., 2020). Despite this, advanced technologies are crucial for reducing environmental pollution, and ICT offers efficient solutions for businesses through advanced communication systems. While some studies suggest that the Internet consumes electricity and contributes to environmental degradation, others argue that it can be helpful to enhance energy efficiency and reduce environmental degradation (Wolfram et al., 2021)."

2.3 Green Initiatives, Natural Resource Utilization, and Environmental Impact

Although renewable energy (RE) can reduce environmental pollution, the findings are mixed. Research has shown that RE usage has decreased carbon emissions in emerging economies like China (Sebestyén, 2021). However, other studies have found that RE does not significantly affect environmental pollution in Thailand, Turkey, or Pakistan (Musa et al., 2021). A few studies have also suggested that, while RE may increase CO_2 production in the long run, it does not harm BRICS economies in the short run (Sharif et al., 2020).

The influence of natural resources (nr) on climate change is a complex issue with conflicting findings in the literature. Some studies have found a negligible effect (Yang et al., 2022), a clear correlation (Wang et al., 2022), and even an enhancement of environmental quality (Tawiah et al., 2021) in certain countries. However, other studies have shown that NR depletion increases carbon emissions (Shen et al., 2021), and NR extraction and tourism contribute to carbon emissions (Fu et al., 2020). The relationship between NR and pollution depends on various factors, including the type of resource, the country's level of development, and the use of fossil fuels. For example, in developed countries, metal and ore resources can improve environmental pollution, whereas energy and renewable resources can reduce pollution. However, industrialization has exacerbated ecological pollution in these countries. The reverse is true for developing countries, where emissions decrease as fuel and renewable resource availability increase (Xing et al., 2019). Wang et al. (2022) found a statistically significant reduction in carbon emissions in Pakistan through NR rent. However, Ahmad et al. (2021) estimated that NR abundance increased CO_2 emissions in some Asian countries.

Urbanization, energy use, and GDP significantly contribute to environmental pollution in both developed and developing countries. A study (Sharmin, 2022) on developing countries from 1965 to 2006 found unidirectional causality between GDP and carbon emissions and suggested a switch to clean energy. This study found bidirectional causality between climate change and economic growth and identified the potential impact of carbon mitigation on India's GDP. Naseem et al. (2022) found a connection between economic progression and the ecological footprint (EF), suggesting that economic growth leads to increased EF.

More research is needed to explore the connections between institutional quality, natural resources, sustainable economic growth, green index, technological innovation, and environmental sustainability. Current literature needs to address this gap. However, various studies have advocated the affiliation of renewable energy, sustainable development, technology, and natural resources. However, the factors as an index have yet to be employed, such as the green index, institutional quality index, technological innovation index, and the interaction between institutional quality and technological innovation. Integrating digitalization into environmental sustainability analysis is a relatively underexplored area in current research. While digitalization is often studied regarding its economic and social impacts, its potential to drive environmental sustainability—particularly in emerging economies—has not been thoroughly examined. Nevertheless, this may be one of the pioneering works investigating the impact of institutional quality, natural resources, sustainable economic growth, the green index, technological innovation, and environmental sustainability of BRICS between 1990 and 2021.

To provide a robust framework for the literature review, we will incorporate a theoretical background section at the beginning. For example, sustainable development theory covers sustainable development's foundational concepts, including the balance between economic growth, environmental protection, and social equity. Similarly, institutional theory is discussed in the context of how institutional structures and governance influence environmental policies and their effectiveness. Finally, innovation and technology adoption theories provide a basis for understanding how technological advancements can drive or impede progress toward sustainability.

Like many existing studies, this research emphasizes the importance of environmental sustainability in the context of emerging economies. However, the study uses panel data and advanced econometric methods, such as quantile regression and FMOLS, consistent with existing literature that provides robust empirical evidence on the relationships between various economic and environmental factors. Similarly, unlike many studies focusing on traditional environmental factors, this research uniquely integrates digitalization as a critical variable influencing sustainable development. This adds a contemporary dimension to the analysis, reflecting the growing impact of digital technologies on environmental outcomes.

3 Methodology

Climate change and environmental degradation are phenomena worldwide; global temperature rises annually. Therefore, a panel dataset is organized to assess the influence of the institutional quality index, green index, sustainable development, technological innovation index, and natural resources on the environmental index, which are collected from the World Development Indicators (WDI), Global Footprint Network (GFN), Green Growth Index (GGGI), and International Country Risk Guide (ICRG). A complete description of these factors is presented in Table 1.

Therefore, the current study organized the green index (green tax, green energy, and green innovation), institutional quality index (government effectiveness and political stability no violence), natural resources (oil, gas, and forest rent), digital economy index (high-tech, fixed telephone, and mobile subscriber), economic growth, environmental quality index (ecological

Table 1 Description of Factors

Symbol			Description	Measurements unit	Source
evnind1	Environ Index	EFP	Ecological footprint	Global hector per capita	GFN
		CO2	Carbon emission	(Metric tons per capita)	WDI
seg3		SEG	Sustainable development	% Of Total Energy consumption	WDI
iqinde6	Institutional Quality	GE	Government effectiveness		ICRG
		PSNV	Political stability No violence		ICRG
nrr5		NR	Natural resource	(% of GDP)	WDI
	Green Index	GR	Green energy	Renewable energy consumption (% of total final energy consumption)	WDI
gnn4		GRT	Green tax	Per capita (% of gdp)	GGGI
		GRI	Green innovation	Per capita (% of gdp)	GGGI
	Tech Innovation	Digital Evolution	Mobile cellular subscriptions (per 100 people)		WDI
techind2			Fixed telephone subscriptions (per 100 people)		WDI
			High-technology exports (% of manufactured exports)		WDI
	Mineral extraction		Domestic extraction (Biomass)		Resource efficiency
mret8			Domestic extraction (Fossil Fuels)		Resource efficiency
			Domestic extraction (Metal Ores)		Resource efficiency
			Domestic extraction (Non-Metal Ores)		Resource efficiency

footprint and carbon emission), and an interaction term gnn*iq is employed for BRICS economies for ecological sustainability. For this objective, a panel dataset of BRICS comprised of 1990–2021 contained the WDI, environmental footprint, and ICRG.

The interaction term gnn*iq serves as a proxy for ecological sustainability because it encapsulates the idea that the success of green policies (such as green energy adoption or innovation) heavily depends on the institutional environment in which they are implemented. Strong institutions (high iq) are more likely to enforce environmental regulations effectively, promote green innovation, and ensure that taxes are efficiently collected and utilized. Conversely, even well-designed green initiatives may fail to achieve desired environmental outcomes in countries with weak institutions. Therefore, the gnn*iq term reflects a more holistic measure of ecological sustainability, as it accounts for both the direct impact of green initiatives and the moderating effect of institutional quality on these initiatives. This interaction provides deeper insights into the conditions under which green policies most likely contribute to sustainable development, particularly in the context of BRICS nations, where institutional strength varies widely.

3.1 Theoretical Relationship of Dependent and Independent Variables

The Socio-Technical Systems Theory is the most appropriate choice for the given parameters of "Digital Evolution, Green Initiatives, and Institutional Instruments." Based on the following reasons. First, this theory emphasizes the relationship between social and technical systems, making it suitable for analyzing how digital technologies (technical) interact with social structures and institutional frameworks (social) to promote green initiatives. Secondly, it accounts for the complexities in implementing digital solutions and green policies, recognizing that technological advancements and institutional changes are necessary for successful outcomes. Third, the theory supports understanding how institutions can adapt to technological changes while promoting sustainable practices. Finally, it is particularly useful in the context of BRICS nations, where diverse social, economic, and institutional factors come into play in pursuing sustainable development. Thus, using the Socio-Technical Systems Theory, this study can comprehensively explore the synergies and tensions between digital evolution, green initiatives, and institutional instruments.

Although the Socio-Technical Systems Theory doesn't have a single mathematical expression but can be represented through several conceptual frameworks that illustrate the interactions between social and technical components. However, the two most ways to express its core idea mathematically are through system dynamics and feedback loop models:

3.2 System Dynamics Model

$$S_t = f(T(t), C(t), I(t))$$

Here S_t System performance (socio-technical outcomes), ($T(t)$ Technical factors (e.g., technology adoption rate, digital tools), $C(t)$ Social factors (e.g., user engagement, cultural attitudes), and $I(t)$ Institutional factors (e.g., policies, regulations).

3.3 Feedback Loops Model

Now, in the case of Feedback loops where, interaction can be modeled with it as follows:

$$\frac{dS}{dt} = \alpha T(t) + \beta C(t) + \gamma I(t)$$

Here, α, β, γ are coefficients representing the influence of each factor, which expressions emphasize the dynamic and interdependent nature of social and technical systems, reflecting the holistic approach of the theory.

Figure 2 of the Socio-Technical Systems Theory illustrates the interconnections between the three main components: Technical Factors, Social Factors, and Institutional Factors, all contributing to the overall System Performance. This diagram captures the dynamic interactions inherent in socio-technical systems. Finally, here is the visual representation of the Socio-Technical Systems Theory, incorporating the parameters from this study. The components "Digital Evolution," "Green Initiatives," and "Institutional Instruments" are depicted as interrelated elements contributing to the outcome: "Sustainable Development" and "Environmental Sustainability" for BRICS nations.

The bar plot (Fig. 3) represents the mean environmental index (`evnind1`) for five countries: India, China, South Africa, Brazil, and Russia. The length of each bar corresponds to the average value of the environmental index for each country, providing insights into their relative environmental performance or sustainability levels. This bar plot effectively illustrates the varying levels of environmental performance among the five countries, providing insights into the underlying economic and environmental dynamics. It underscores the need for countries to adopt sustainable development practices, balance economic growth with environmental protection, and address unique challenges to enhance their overall environmental quality.

Finally, the model is mathematically expressed.

$$\begin{aligned} \ln evnind1_t = \kappa_0 + \kappa_1 \ln technind2_{it} + \kappa_2 \ln seg3_{it} + \kappa_3 \ln gnn4_{it} + \kappa_4 \ln nrr5_{it} \\ + \kappa_5 \ln iqinde6_{it}\kappa_6 \ln gnn * iq7 + \kappa_7 mret8_{it} + \mu_{it} \end{aligned} \tag{1}$$

where i, t, and characterize the years, cross-sections, error terms, and coefficient values. "The CD test is the first step in analyzing interdependence between panel series. In addition, the test results provide insights into which econometric techniques are used to calculate the cointegration and long-run coefficients. Pesaran (2015) introduced the CD test. Mathematically, it is expressed as."

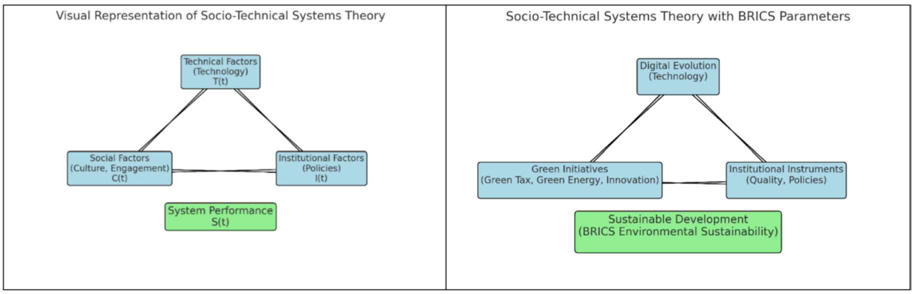

Fig. 2 Visual presentation of Socio-Technical Systems Theory concerning current study

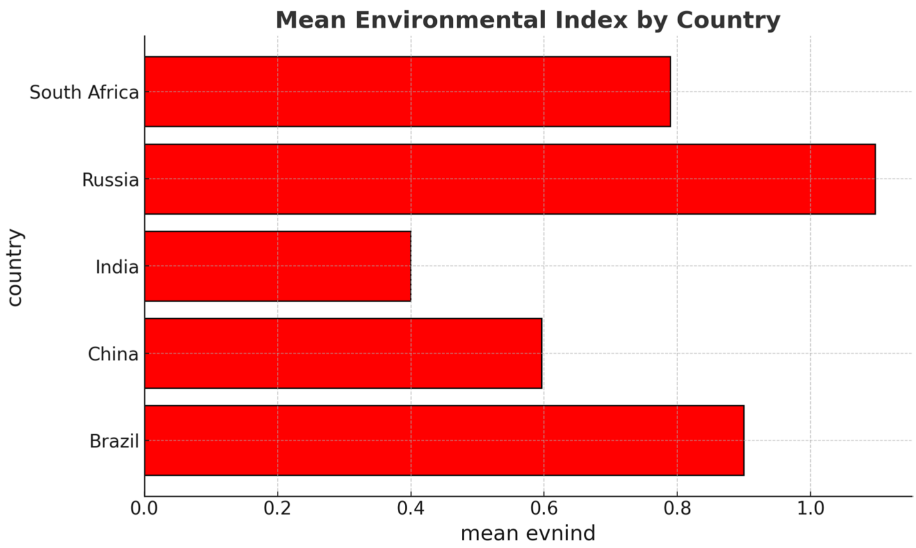

Fig. 3 Mean of dependent variables for each country

$$PCD = \sqrt{\frac{2S}{H(H-1)}}\left(\sum_{i=1}^{n-1}\sum_{j=i+1}^{n}\phi^{ij_t}\right) \tag{2}$$

S, H, and φ denote the time, cross-section, and error terms, respectively. Pesaran, 2021) outlined the nature of panel data in the equations.

$$\widetilde{\Delta} = \sqrt{C}\left(\frac{C^{-1}\widetilde{A} - G}{\sqrt{2G}}\right) \tag{3}$$

$$\widetilde{\Delta}_{\text{adj}} = \sqrt{C}\left(\frac{C^{-1}\widetilde{A} - E(\widetilde{Z}_{\text{iT}})}{\sqrt{var(\widetilde{Z}_{\text{iT}})}}\right) \tag{4}$$

It is essential to execute 2nd generation unit-root testing if the results suggest the presence of a structural break. The CIPS and cross-sectionally augmented Dickey-Fuller were considered for this purpose. The integration sequence was tested between evn, iq, gnn, seg, tech, nr, and gnn*iq. This study employs the Kao, Pedroni, and Westerlund (2005) tests to determine the cointegration level among the parameters.

Kao examines the occurrence of cointegration among a set of variables. It is based on the eigenvalue ratio approach and provides a method to test for cointegration among a group of time-series variables. The Kao test statistic was computed based on the eigenvalues of a matrix derived from the regression residuals. The Kao cointegration test is widely used in econometrics and finance to analyze the behaviour of the parameters. In addition, the test is known to detect co-integration even in small sample sizes, making it a valuable tool for researchers working with limited datasets, and it is mathematically expressed as.

$$\Omega = \lim_{T\to\infty} \frac{1}{T} E\left(\sum_{t=1}^{T} w_{it}\right)\left(\sum_{t=1}^{T} w_{it}\right) = \Sigma + \Gamma + \Gamma' = \begin{bmatrix} \alpha^2_{ou} & \alpha^2_{ou\varepsilon} \\ \alpha^2_{ou\varepsilon} & \alpha^2_{ou\varepsilon} \end{bmatrix} \tag{5}$$

$$\widehat{\eta} it = \kappa \widehat{\eta}_{it-1} + \sum_{j=1}^{n} \phi \Delta \widehat{\eta}_{it-j} + v_{itp}$$

Pedroni cointegration is based on the residual-based cointegration approach and provides a method to test for cointegration among a set of time-series variables.

$$P\alpha = T\sqrt{N}\left(\sum_{i=1}^{N}\sum_{t=1}^{T} \widehat{L}^{-2}_{1i\widehat{\varepsilon}i,t-1})^{-1} \sum_{i=1}^{N}\sum_{i=1}^{T} \widehat{L}^{-2}_{1i\widehat{\varepsilon}i}(\widehat{\varepsilon}_{i,t-1}\Delta\widehat{\varepsilon}_{i,t} - \widehat{\lambda}_i\right) \tag{6}$$

The Westerlund test is often used in econometric and financial studies to examine the long-run relationships between economic variables.

Zhu et al. (2020) found that the quantile regression approach is appropriate for analyzing the relationship between variables with varying integration levels based on the quantiles of the dependent variables. The Quantile regression model was used to study the extreme values of the conditional variable distributions. Therefore, understanding the regression process, which is a precursor of the quantile regression model, is essential.

The regression model is defined as $S_t = \beta * + \sum_{j=1}^{h} \gamma_{j*} S_{t-j} + \sum_{j=0}^{p} \kappa_{j*}\prime D_{t-j} + \lambda_t$ where h and p denote the lags and λ for the white noise, the general description of quantile regression is as follows.

$$S_t = \beta * (\rho) + \sum_{j=1}^{h} \gamma_{j*}(\rho) S_{t-j} + \sum\nolimits_{j=0}^{p} \kappa_{j*}\prime(\rho) D_{t-j} + \lambda_t(\rho) \tag{7}$$

The next step involves estimating long-run parameters using the plug-in principle.

$$\widehat{\lambda}_{(\Gamma)} = \widehat{\rho}_{(\Gamma)}(1 - \sum\nolimits_{j=i}^{p} \kappa_{(\Gamma)})^{-1} \tag{8}$$

4 Estimation and Results

Technological innovation, the green index, sustainable economic development, natural resources, institutional quality, and the green index* institutional quality are organized to measure their influence on the environmental index. Nowadays, the environment is a severe concern in developing nations' forums. Therefore, the study employed the latest dataset to measure the influence of predators on the environmental indices. For this purpose, the initial research used descriptive analysis to elaborate on the features of the related factors. The results are reported in Table 2.

As detailed in Table 2, the central tendency includes the maximum, minimum, and mean values, highlighting that each dataset segment's midpoint lies between its extremes. Standard deviation, which measures how values spread from the mean, ideally falls within a range of ±2. Skewness quantifies the asymmetry in data distribution; a positive skew indicates a longer right tail, while a negative skew indicates the opposite. The data revealed a positive skew within the acceptable range of ±3. Kurtosis, measuring the distribution's

Table 2 Descriptive analysis

Stats	evnind1	techind2	lnseg3	gnn4	lnnrr5	iqinde6	gnn*iq7	mret8
N	160	160	160	160	160	160	160	160
Mean	0.722628	1.283373	1.40053	− 0.0034769	1.389404	1.196945	− 0.0115153	0.1766373
Min	0.1036125	0.029366	− 2.17989	− 0.7060868	− 0.0527659	0.2109123	− 0.8925294	0.0001887
Max	1.518181	2.965056	2.676291	1.418182	3.090883	2.133493	1.140273	1
SD	0.3865716	0.7467169	0.905496	0.3259258	0.7304014	0.2972231	0.3637023	0.2473911
Skewness	− 0.1646284	0.1954883	− 1.499982	0.662561	0.4567325	0.3408861	0.0206506	1.845785
Kurtosis	1.989834	2.116293	5.738972	4.958182	2.680509	3.371434	3.408815	5.487066
J- Bera	0.0232	0.0445	0.3031	0.109	1.926	0.1341	0.5696	2.129

peakedness, also remained within the standard range of ± 10. Skewness and kurtosis helped identify outliers in the dataset. Additionally, the Jarque–Bera test, which checks for normality in regression model residuals based on skewness and kurtosis, used a P-value threshold (typically 0.05) to indicate significant deviations from normality.

4.1 Panel Data Pre- Diagnostics

Table 3 presents diagnostic tests for the data. The Breusch-Pagan/Cook-Weisberg test for heteroskedasticity produced a Chi-squared statistic of 5.29 with a *p* value of 0.0214, below the 0.05 significance level. This leads to rejecting the null hypothesis of homoskedasticity, indicating that error variance is not constant, potentially affecting the regression estimates. The Wooldridge test for autocorrelation in panel data showed an F-statistic of 7.136 with a *p* value of 0.0756, above the 0.05 threshold, meaning there is no evidence of autocorrelation. Finally, endogeneity tests indicate that the variables are endogenous since the p-values are well below 0.05, suggesting that instrumental variable techniques may be needed to address endogeneity issues.

Furthermore, our analysis regulated the stationarity in the series, and for this purpose, second-generation unit-root tests are described in Table 4.

The results of (CIPC) in Table 4 demonstrate that techind2TECH and lnseg3SEG are stationary at the same level. However, (PSADF) reveals that seg is 1%, whereas gnn, nrr, and gnn*iq are at the 10% and 5% significance levels, respectively. Furthermore, all elements have constant variance at the first difference and zero means. Consequently, it can be concluded that all the series are stationary at the first difference.

The information mentioned above in Fig. 4 reports the various behaviors of the underlined variables of the study from the BRICS. The moderate correlation observed between techind2 (technological innovation index) and evnid1 (environmental index) is expected, given that technological innovations, such as cleaner production methods and energy-efficient technologies, directly improve environmental quality by reducing emissions and optimizing resource use.

In Table 5, VIF indicates how much coefficient variance is inflated due to multicollinearity with other variables. Typically, a VIF above 10 suggests high multicollinearity, but in this case, all values are well below that threshold, indicating low multicollinearity among the variables. Thus, here, no issue of severe multicollinearity has been detected in the dataset; although each country behaves differently from the perspective of its respective variables, it is still necessary to verify cross-sectional independence before attempting

Table 3 Tests for heteroskedasticity, autocorrelation, and endogeneity

Breusch–Pagan/Cook–Weisberg test for Heteroskedasticity	
chi2(1)	5.29
Prob > chi2	0.0214
Wooldridge test for Autocorrelation	
F (1 3)	7.136
Prob > F	0.0756
Tests of endogeneity	
H0: Variables are exogenous	
Durbin (score) chi2(1)	13.2526 (p = 0.0003)
Wu-Hausman F(1,153)	13.8172 (p = 0.0003)

Table 4 Second-generation unit root

	CIPS		PSADF	
Variables	Level	difference	Level	difference
evnind1	**– 0.294**	**– 4.031*** **	**– 0.746**	**2.043*** **
techind2	**– 1.48**	**– 2.996*** **	**– 3.471**	**– 3.15*** **
lnseg3	**– 3.958**	**– 6.082** **	**– 2.578**	**– 4.754*** **
gnn4	**– 3.203**	**– 6.01** **	**– 2.44**	**– 5.396** **
lnnrr5	**– 1.909**	**– 5.489** **	**– 2.151**	**– 4.759** **
iqinde6	**– 3.199**	**– 6.069** **	**– 2.511**	**– 5.478** **
gnn*iq7	**– 3.477**	**– 6.109** **	**– 2.451**	**– 5.494* **
mret8	**– 0.909**	**-3.489** **	3.687	2.074***

***$p<0.01$, **$p<0.05$, *$p<0.1$

p ≤ 0.01: This suggests a very low probability (1% or less) that the observed result is due to random chance

p ≤ 0.05: Representing a statistically significant result with a 5% or lower probability that the result is due to chance. This is often used as the standard threshold for significance

p ≤ 0.1: Indicating a marginally significant result. Here, there is a 10% or lower chance that the observed result occurred by random variation, which is sometimes acceptable

short- and long-run examinations. Therefore, this study employed average correlation coefficients and Pesaran's (2004) CD test (Pesaran, 2021). The test is based on decomposing the panel data into long-run and short-run components, and it tests the null hypothesis of no CSD against alternative CSD. The results are shown in Table 6.

The analysis (Table 6) depicts these cross-sections as independent, rejecting the null hypothesis of the CSD. Furthermore, the p-values for evn, tech, gnn, seg, nrr, iq, and gnn*iq in the CD test are significant at the 1% level. As a result, the variance in the data is quite comparable because the relevant variables move similarly.

One of the reasons for choosing Model 1 is that the mean of the dependent variable in the study varies according to the country and year (Fig. 5), which means that OLS cannot be applied, and different methods should be used. Notably, Russia and Brazil exhibit relatively high EI values with greater variability (heterogeneity) compared to other countries, which can be attributed to the interplay of geographical diversity, economic activities, varying policy enforcement, regional development disparities, indigenous community influence, and climate change impacts. Addressing these disparities requires tailored regional policies, equitable environmental governance, and sustainable development practices that consider each area's unique ecological and socio-economic contexts.

Next, the study employed slope homogeneity, which assumes that the coefficients of a regression model are the same for all cross-sectional units in a panel dataset. The estimations of the slope homogeneity are reported in Table 7.

The estimations (Table 7) show that all the concerning factors' slopes are homogeneous at a 1% significance level. Next, the study utilized panel cointegration (Kao, Pedroni, and Westerlund) to determine the long-term affiliation among the factors; the outcomes are reported in Table 8. The final decision on the presence of a long-term relationship will be based on the results of the Westerlund cointegration test, which is known for its robustness, especially in small sample sizes. If the Westerlund test indicates cointegration at a significant level, it confirms a long-term relationship between the variables.

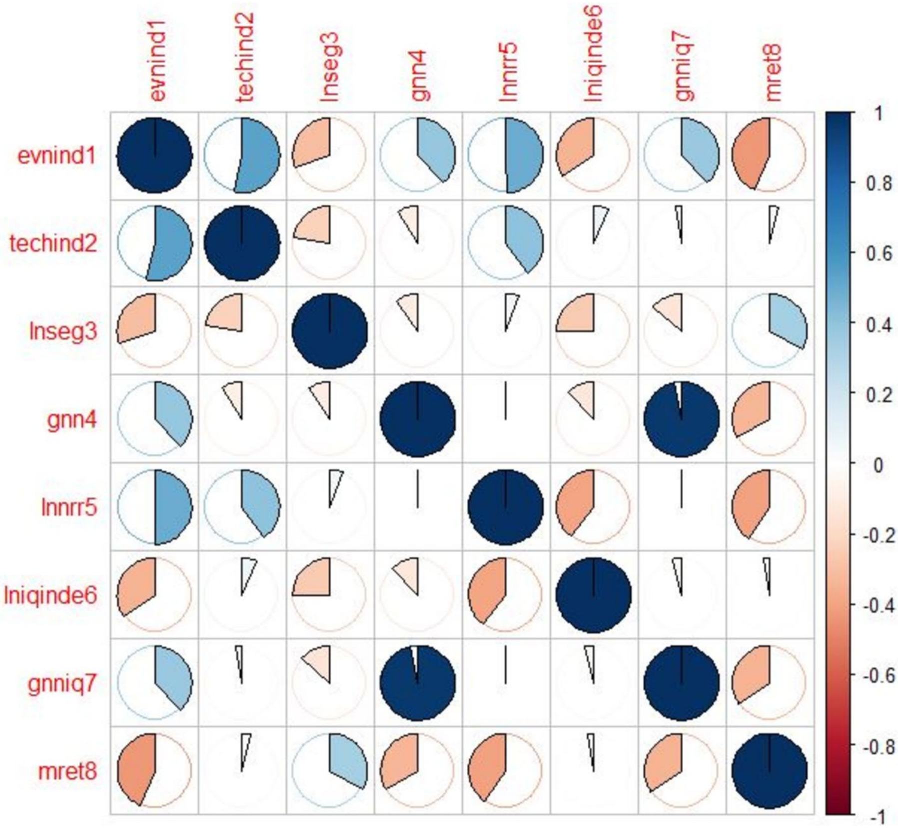

Fig. 4 Graphical Trends of correlation matric of the dataset

Table 5 Variance inflation factor (VIF)

Variables	VIF	1/VIF
lngnn4	3.212	0.311
gnn*iq7	2.973	0.336
techind2	1.919	0.521
nrr5	1.901	0.526
iqinde6	1.772	0.564
mret8	1.546	0.647
seg3	1.314	0.761
Mean VIF	2.091	

The results (Table 8) advocated that long-term affiliation prevails among the parameters. The cointegration test results clearly show the robust and enduring relationships among the variables under examination. The data confirm strong cointegration among evn, tech, gnn, nrr, seg, iq, and gnn*iq, indicating that these factors are inextricably linked in the long term. In other words, the data suggest that these variables move in harmony, in concert

Table 6 Average Correlation Coefficients & Pesaran (2015) CD test

Variables	CD test	*p* value	Average joint T	Mean (*p*)	Means abs (*p*)
evnind1	0.108	0.914	32	0.01	0.55
techind2	16.954***	0	32	0.95	0.95
lnseg3	4.015***	0	29.79	0.24	0.26
gnn4	3.194***	0.001	32	0.18	0.23
lnrr5	9.582***	0	32	0.54	0.54
iqinde6	0.393	0.694	32	0.02	0.37
gnn*iq7	2.515***	0.012	32	0.14	0.23
mret8	15.596***	0	32	0.87	0.87

Under the null hypothesis of cross-section independence, CD ~ N(0,1)

P values close to zero indicate data are correlated across panel groups. Furthermore, *, **, *** indicate 10%, 5%, and 1% significance level

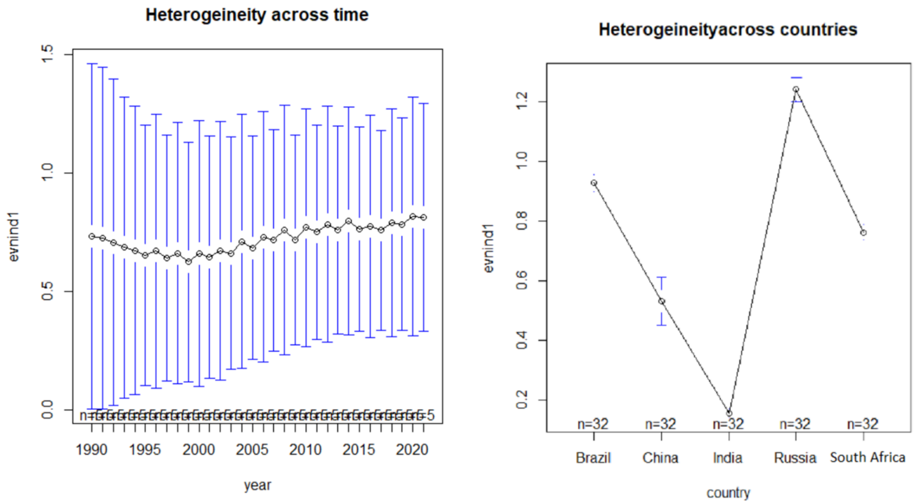

Fig. 5 Overview of environmental index

Table 7 Slope homogeneity

H0: slope coefficients are homogenous		
	Delta	*p* value
	8.538***	0.00
Adj	9.924***	0.00

***$p<0.01$, **$p<0.05$, *$p<0.1$

with one another, over the long run. Tables 9, 10, and 11 present the estimation of the underlying variables based on the latest available econometric model.

Moreover, as shown in the following figures, the study discloses the adoption and trend of the study factors in BRICS economies from the 90 s to 2021.

Table 8 Tests for cointegration

Kao Cointegration	Statistic	*P* value
Modified Dickey-Fuller t	−2.6463***	0.0041
Dickey-Fuller t	−3.1515***	0.0008
Augmented Dickey-Fuller t	0.0307**	0.0477
Unadjusted modified Dickey-Fuller t	−8.3254***	0.0000
Unadjusted Dickey-Fuller t	−5.0307***	0.0000
Pedroni Cointegration		
Modified variance ratio	−3.1017***	0.0010
Modified Phillips–Perron t	−1.8602**	0.0314
Phillips–Perron t	−7.2868***	0.0000
Augmented Dickey-Fuller t	−9.6268***	0.0000
Westerlund test		
Variance ratio	2.6988***	0.0035

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 9 Model 1 (Newey-West Standard Error Regression), Model 2 (Multivariate Regression), and Model 3 (Mixed Regression Model)

Variable	Model 1	Model 2	Model 3
techind2	0.260***		0.260***
	−0.0301		−0.0276
seg3	−0.0157***	−0.0278***	−0.0157***
	−0.0053	−0.0062	−0.005
gnn4	0.351***	0.399***	0.351***
	−0.0626	−0.0705	−0.0557
nrr5	0.0124**	0.0421***	0.0124**
	−0.0051	−0.0056	−0.0054
iqinde6	−0.388***	−0.160*	−0.388***
	−0.0725	−0.0852	−0.0712
mret8	−0.465***	−0.173*	−0.465***
	−0.0874	−0.102	−0.0857
Const	0.950***	0.862***	0.950***
	−0.112	−0.138	−0.109
Obser	160	160	160
R-square		0.561	

Standard errors in parentheses, ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Environmental quality (Fig. 6) in BRICS economies (Brazil, Russia, India, China, and South Africa) is a complex issue that affects both economic development and the well-being of their populations. Although these economies have boosted economic growth, their rapid expansion has come at the cost of environmental degradation, including air and water pollution, deforestation, and soil degradation. As a result, BRICS economies are among the most significant suppliers of global CO_2 and environmental problems and face the challenge of balancing economic growth with ecological sustainability. Technological innovation (Fig. 6) has driven BRICS' economic development and competitiveness of BRICS countries. Over the last several decades, these nations have invested heavily in R&D and

Table 10 (Model 3SLS)

VARIABLES	Model 1	Model 2
techind2	0.260***	0.199***
	−0.0276	−0.0293
seg3	−0.0157***	−0.0108*
	−0.005	−0.0056
gnn4	0.351***	
	−0.0557	
nrr5	0.0124**	0.0293***
	−0.0054	−0.005
iqinde6	−0.388***	
	−0.0712	
mret8	−0.465***	−0.320***
	−0.0857	−0.0911
gnn*iq7		0.342***
		−0.0547
Constant	0.950***	0.426***
	−0.109	−0.0497
Obser	160	160
R-square	0.718	0.641

***$p<0.01$, **$p<0.05$, *$p<0.1$

innovation ecosystems, including technology parks and incubators. They also worked to connect academics, businesses, and the government to facilitate the transfer of lab-to-market knowledge and technology. However, China and India are leading technological innovations and integration into the global economy, whereas Brazil and Russia struggle to create an innovation-friendly corporate climate.

Based on the above theoretical and dataset narrations, this study utilized multiple panel data models to make strategic decisions to capture the complexity and dynamic nature of the relationships between digitalization, institutional quality, green initiatives, and environmental sustainability in BRICS nations. The use of multiple panel data models is justified by the need to account for the complex, dynamic, and multifaceted nature of the studied relationships. For example, Newey-West standard errors are robust to both heteroskedasticity and autocorrelation, making them suitable for the above scenario, especially given the presence of autocorrelation in the dataset. Similarly, multivariate regression, provided the model is correctly specified and assumptions are addressed, while mixed regression models allow for the effective capture of both fixed and random effects. This approach strengthens the robustness of the findings and provides a comprehensive understanding of how digitalization, institutional quality, and green initiatives interact to influence environmental sustainability in BRICS nations.

4.2 Key Analysis

Table 9 presents the results of multiple regression models analyzing the relationship between economic and environmental variables across BRICS countries. Various models such as Newey-West, multivariate, and mixed regressions are used. The technological

Table 11 Quantile regression estimation

Long Run											
	Variable	Coefficient	Std. Err	t− stat	Prob		Variable	Coefficient	Std. Err	t-stat	Prob
	GNN	0.5619	0.2777	2.0235	0.0447		GNN	1.3538	0.3057	4.4293	0
$q = 0.25$	IQ	0.0442	0.0317	2.3963	0.0646	$q = 0.75$	IQ	0.098	0.0426	2.2989	0.0229
	TECH	0.2865	0.0309	9.2653	0.0000		TECH	0.2699	0.0368	7.3306	0
	SEG	−0.0025	0.0039	−0.6404	0.5228		SEG	−0.0047	0.0041	−1.1514	0.2514
	NRR	0.0267	0.0068	3.9329	0.0001		NRR	0.0428	0.0055	7.7265	0
	MRET	0.6732	0.1619	−4.1567	0.0001		MRET	−0.3793	0.1895	−2.0012	0.0474
	GNN*IQ	−0.0889	0.2423	−2.3669	0.7142		GNN*IQ	−0.7044	0.2583	−2.7268	0.0071
	GNN	1.8617	0.365	5.1003	0.0000		GNN	2.1785	1.2258	1.7773	0.0775
$q = 0.5$	IQ	0.1483	0.047	3.154	0.0019	$q = 0.95$	IQ	0.773	0.1485	5.2036	0
	TECH	0.2867	0.0382	7.5049	0.0000		TECH	0.0805	0.0974	0.8267	0.4097
	SEG	−0.0056	0.0054	−1.0499	0.0254		SEG	−0.022	0.012	−1.839	0.0678
	NRR	−0.0505	0.0063	−8.0212	0.0000		NRR	−0.0525	0.0097	−5.394	0
	MRET	−0.6312	0.1918	−3.2910	0.0013		MRET	−0.0580	0.2240	−0.2591	0.7959
	GNN*IQ	−1.0956	0.3182	−3.4429	0.0007		GNN*IQ	−1.6806	1.7894	−0.9392	0.3491
Short Run											
	D(GNN)	0.0826	0.0436	1.8932	0.0604		D(GNN)	0.0522	0.0774	0.6738	0.5015
	D(GNN*IQ)	−0.0653	0.0386	−1.69	0.0933		D(GNN*IQ)	−0.0398	0.0605	−0.6587	0.5112
	D(IQ)	−0.0088	0.0165	−0.5335	0.5946		D(IQ)	−0.0042	0.0251	−0.1685	0.8665
	D(NRR)	0.0056	0.0022	2.5639	0.0114		D(NRR)	0.0055	0.0027	2.0161	0.0457
	D(SEG)	−0.0008	0.0012	−0.6834	0.4955		D(SEG)	−0.0001	0.0015	−0.0805	0.936
	D(TECH)	0.0477	0.0528	0.904	0.3676		D(TECH)	0.0675	0.0717	0.9407	0.3485
	D(MRET)	1.1494	3.3454	0.3435	0.7317		D(MRET)	−0.6283	0.367	−1.7120	0.0893
$q = 0.25$	D(EVN(-1))	−0.8162	0.0916	−8.9106	0.0000	$q = 0.5$	D(EVN(-1))	−0.7611	0.1218	−6.2508	0
	D(GNN(-1))	0.1053	0.0309	3.4034	0.0009		D(GNN(-1))	0.059	0.1805	0.327	0.7441

Table 11 (continued)

Long Run											
	Variable	Coefficient	Std. Err	t− stat	Prob		Variable	Coefficient	Std. Err	t-stat	Prob
	D(GNN*IQ(-1))	−0.0786	0.0279	−2.8149	0.0056		D(GNN*IQ(-1))	−0.0465	0.1286	−0.3615	0.7183
	D(IQ(-1))	−0.046	0.0203	−2.266	0.025		D(IQ(-1))	−0.0266	0.0322	−0.8257	0.4104
	D(NRR(-1))	0.0031	0.0017	1.8674	0.064		D(NRR(-1))	0.0021	0.0024	0.8589	0.3919
	D(MRET(-1))	2.2964	3.5345	0.6497	0.5171		D(MRET(-1))	3.2314	1.8912	1.7086	0.0899
	D(SEG(-1))	−0.0006	0.0016	−0.3873	0.6992		D(SEG(-1))	0.0000	0.002	0.0205	0.9837
	D(TECH(-1))	−0.1405	0.0437	−3.2159	0.0016		D(TECH(-1))	−0.0231	0.064	−0.3617	0.0181
	D(GNN)	0.0231	0.1309	0.1767	0.86		D(GNN)	−0.0053	0.0446	−0.1197	0.9049
	D(GNN*IQ)	−0.0126	0.0966	−0.1307	0.8962		D(GNN*IQ)	0.0108	0.0363	0.2984	0.7659
	D(IQ)	0.0275	0.0262	1.049	0.296		D(IQ)	0.0507	0.0132	3.8393	0.0002
	D(NRR)	0.0062	0.0021	2.8985	0.0044		D(NRR)	0.0033	0.0025	1.3033	0.1946
	D(MRET)	−0.3651	0.2277	−1.6033	0.1113		D(MRET)	1.8423	3.6716	0.5018	0.6167
	D(SEG)	−0.0004	0.0012	−0.3319	0.7405		D(SEG)	−0.0009	0.0006	−1.5024	0.1353
$q=0.75$	D(TECH)	0.0971	0.0545	1.7814	0.0771	$q=0.95$	D(TECH)	0.1536	0.0247	6.2235	0
	D(EVN(-1))	−0.7182	0.1009	−7.1209	0		D(EVN(-1))	−0.5731	0.0589	−9.7259	0
	D(GNN(-1))	0.0627	0.1642	0.3817	0.7033		D(GNN(-1))	0.0875	0.0507	1.7249	0.0868
	D(GNN*IQ(-1))	−0.0472	0.12	−0.3936	0.6945		D(GNN*IQ(-1))	−0.0606	0.0388	−1.5618	0.1206
	D(IQ(-1))	−0.0012	0.0325	−0.0383	0.9695		D(IQ(-1))	−0.0103	0.0181	−0.5668	0.5718
	D(NRR(-1))	0.0004	0.0022	0.2018	0.8404		D(NRR(-1))	−0.0044	0.0018	−2.398	0.0178
	D(SEG(-1))	−0.0016	0.0017	−0.9435	0.3471		D(SEG(-1))	−0.0013	0.0009	−1.4614	0.1462
	D(MRET(-1))	−0.1253	1.5821	−0.0792	0.937		D(MRET(-1))	0.4867	3.5165	0.1384	0.8901
	D(TECH(-1))	0.1094	0.0725	1.5096	0.1334		D(TECH(-1))	0.204	0.0357	5.7179	0

***$p<0.01$, **$p<0.05$, *$p<0.1$

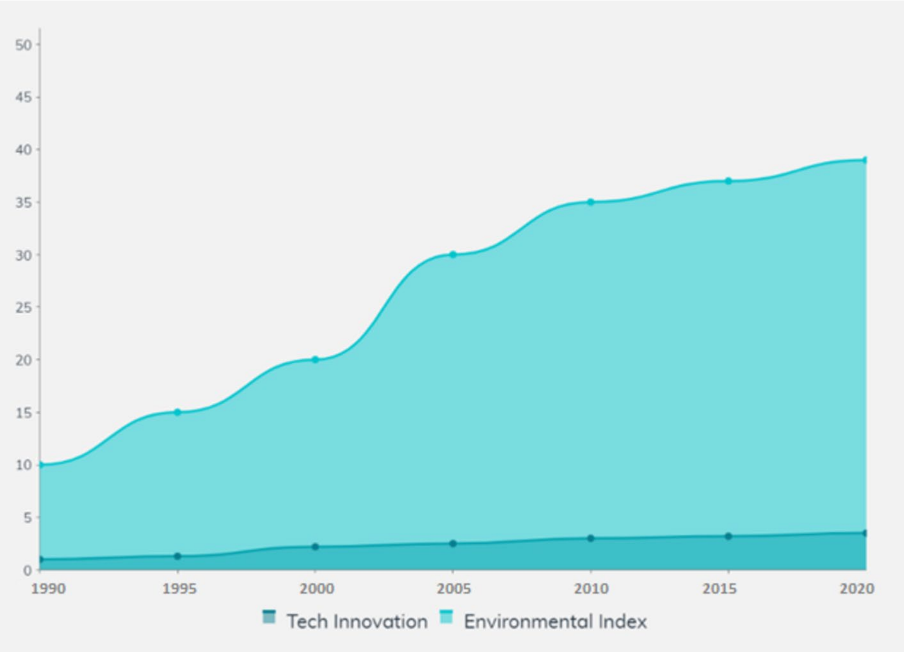

Fig. 6 Overview of environmental index

index (techind) shows a generally positive and significant relationship (e.g., 0.260***) with the outcome variable, indicating that technological advancements, like clean technology, contribute positively to economic or environmental outcomes. The economic growth parameter (seg) consistently shows a negative and significant relationship (e.g., −0.0157***). This suggests that stronger governance may reduce the dependent variable, implying that stricter regulations could constrain economic growth but promote sustainable practices. Green Innovation Index (gnn) has a positive and significant impact (e.g., 0.351***), highlighting that green innovations, such as renewable energy technologies, benefit both economic and environmental outcomes in BRICS countries.

Natural Resource Rent (nrr) displays a positive and significant coefficient (e.g., 0.0124**), indicating that natural resource extraction boosts economic outcomes, although it could pose poorly managed environmental risks. Institutional Quality Index (iqinde) exhibits negative coefficients (e.g., −0.388***), suggesting that higher institutional quality reduces the dependent variable, possibly by enforcing regulations that initially hamper growth but promote long-term sustainability. Finally, mret generally shows a negative relationship (e.g., −0.465***), suggesting that higher market returns may be linked to unsustainable practices.

The 3SLS is well-suited for complex econometric models that require efficient and robust estimation techniques. The fundamental purpose of the 3SLS model involves feedback loops, where changes in one variable can lead to changes in another. When some independent variables are endogenous, it allows for including instrumental variables correlated with the endogenous variables but uncorrelated with the error terms. For example, we use it to influence the interactive term gnn*iq in the techind2.

According to the 3SLS model outcomes in Table 10, green innovation and institutional quality interaction have a positive coefficient for gnniq (e.g., 0.342*** in Model 2), indicating that the interaction between green innovation and institutional quality positively affects the outcome. This suggests that when good governance is combined with innovation in green technologies, it leads to better economic and environmental results.

The regression results suggest that while technological advancements, green innovations, and natural resource rents positively impact economic growth, the effectiveness and sustainability of these outcomes depend significantly on institutional quality and governance. Strong institutions and social governance can enforce regulations that promote sustainability but may initially appear to limit growth. Furthermore, the negative relationship of social and environmental governance with the outcome variable and the positive relationship with green innovation and natural resource management indicate that sustainable growth in BRICS countries requires a balanced approach. Countries must invest in green technologies and improve governance while carefully managing natural resources to avoid long-term environmental degradation. The models emphasize that sustainable economic growth is multifaceted for BRICS countries, involving technology, governance, innovation, and resource management.

The quantile-based regression test examines the relationship between parameters, which can vary across different quantiles of the dependent variables. In addition, the Q-regression test allows for the estimation of different quantile-specific coefficients, meaning that the relationship between the variables crosses other parts of the distribution of the dependent variable. The outcomes of the Q-regression are presented in Table 11.

Table 11 shows that the Green Innovation Index (gnn) positively impacts environmental quality (evn) across all quantiles in BRICS economies, supporting findings by (Iqbal et al. 2021). This suggests that increasing the green index helps improve environmental conditions as BRICS countries invest in green technologies to reduce carbon emissions. Similarly, Institutional Quality (IQ) has a positive effect, with a 1% increase in IQ enhancing environmental quality by 0.1483%, aligning with those reported by (Piabuo et al. (2021). This implies that better institutional quality strengthens green laws and tax policies, reducing emissions and improving environmental outcomes.

Technological innovation also shows a strong positive effect, with a 1% increase boosting environmental quality by 0.2867%, consistent with that of (Haini, 2021), indicating that technological advancements contribute to lowering carbon emissions. On the other hand, using natural resources negatively impacts the environment, with a 1% increase leading to a 0.0505% decline in environmental quality, as supported by Shen et al. (2021). This highlights the environmental risks of overexploiting natural resources in developing economies like BRICS despite their pursuit of sustainability.

4.3 Post-estimation Diagnostics

Post-estimation tests are crucial for verifying the robustness, reliability, and validity of the econometric models used in the study. These tests also help ensure that the assumptions underlying the models are not violated, thereby enhancing the credibility of the results.

This study uses Drisc/Kraay (see Table 12) as a robustness test for regression models presented in Table 9, as it also has the properties to address potential autocorrelation and heteroskedasticity issues effectively. The robustness test outcomes validate the estimation of Table 9.

Table 12 Robustness test (Drisc/Kraay) for Table 9

evnind1	Coefficient	std.err	t	$P > t$	[95% conf	Interval]
techind2	−0.260***	0.030	−8.700	0.000	−0.199	−0.321
seg3	−0.016***	0.006	−2.600	0.014	−0.028	−0.003
gnn4	−0.351***	0.071	−4.950	0.000	−0.206	−0.495
nrr5	−0.167*	0.096	−1.740	0.091	−0.363	−0.028
iqinde6	−0.388***	0.097	−4.010	0.000	−0.586	−0.191
mret8	−0.465***	0.131	−3.550	0.001	−0.732	−0.198
_cons	0.950***	0.166	5.740	0.000	0.613	1.288

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Furthermore, Table 13 presents FMOLS outcomes, which is particularly useful as it deals with cointegrated variables and addresses endogeneity and serial correlation issues in the error terms. It adjusts the ordinary least squares (OLS) regression method to account for cointegration among the variables. Similarly, Dynamic OLS (DOLS) is another regression-based method that addresses the problem of endogeneity and stationarity at differences when estimating the long-run relationship between variables. This accounts for potential feedback effects between the variables and the error term in the regression. Both methods are widely used in econometric research to model the long-run relationship between economic variables and to forecast future trends based on historical data. The outcomes of both models also validate the estimated results generated in Table 10.

Similarly, Table 14 presents FGLS as the robustness test for Table 11 due to its properties in handling issues like heteroskedasticity or Autocorrelation in regression analysis. Thus, the model as a whole is statistically significant, given the low *p* values and the robust Chi-square statistic.

Finally, based on the CUSUSM graph (see Fig. 7), it is possible to conclude that the cumulative sum starts near zero, indicating that the process initially started near the target value, fluctuated around the target value, and remained within acceptable limits of the 5% significance rate. In the case of CUSUMQ, the cumulative total of squares first remains relatively low, showing a constant process variation around the goal value, as seen when examining the CUSUM square chart. Nevertheless, the total of the cumulative squares gradually rises with time, suggesting a systematic variability increase. Similar to the CUSUSM test, the CUSUMQ value also remained within the acceptable limits of the 5% significance rate. Overall, the results of the CUSUM and CUSUMQ confirm that the estimated relationships are robust and consistent over time, as well as the stability of the used model.

Table 13 Robustness test (FMOLS and DOLS) for Model in Table 10

evnind1	FMOLS	DOLS
techind2	− 0.6392	− 0.3453
seg3	− 0.0391	− 0.2845
gnn4	− 0.6068	− 0.1906
nrr5	− 0.3430	− 0.6394
iqinde6	− 0.6094	− 0.3758
gnn*iq7	− 0.8765	− 0.2832
mret8	− 0.2420	− 0.3802

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 14 FGLS Robustness test for Table 11

evnind1	Coef	St.Err	t-value	p value	[95% Conf	Interval]	Sig
lntechind2	−0.188	0.019	−9.94	0.000	−0.151	−0.225	***
lnseg3	−0.068	0.021	−3.29	0.001	−0.108	−0.027	***
gnn4	−0.123	0.049	−2.51	0.012	−0.027	−0.220	***
lnnrr5	−0.090	0.028	−3.26	0.001	−0.036	−0.144	***
lniqinde6	−0.269	0.072	−3.76	0.000	−0.409	−0.129	***
gnn*iq7	−0.356	0.193	−1.85	0.065	−0.022	−0.733	*
lnmret8	−0.068	0.011	−6.01	0.000	−0.090	−0.046	***
Constant	0.548	0.059	9.33	0.000	0.433	0.663	***
Mean dependent var	0.726			SD dependent var	0.392		
Number of obs	154			Chi-square	440.955		
Prob > chi2	0.000			Akaike crit. (AIC)	−44.680		

***p<.01, **p<.05, *p<.1

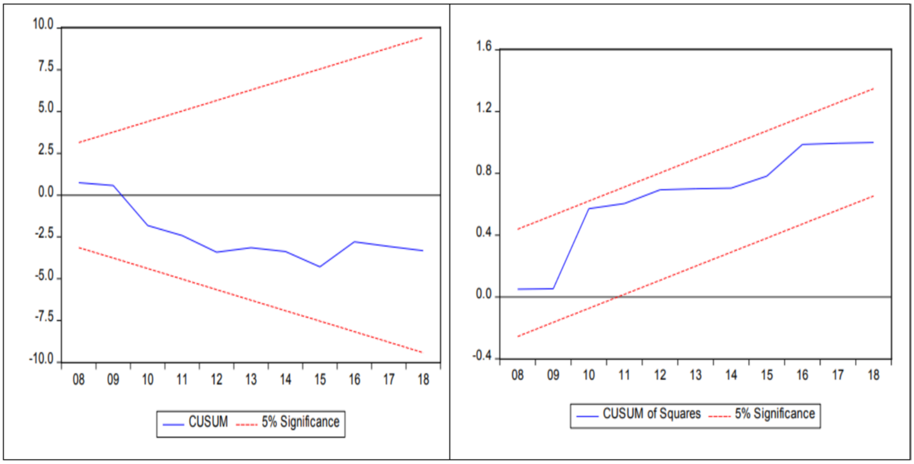

Fig. 7 Cusum and cusum of squares

5 Discussion

Globally, environmental degradation and climate change are escalating owing to human activities. Therefore, developed and developing nations are shifting and adopting enormous green energy, taxes, and innovation to improve environmental quality. Technological innovation, which considerably influences the production sector, significantly affects ecological quality. Moreover, institutional quality, on the other hand, is crucial for the implication of green law. Emerging economies have poor institutional quality and utilize natural resources significantly, ultimately influencing environmental quality.

The green index (comprising a green tax, energy, and innovation) considerably influences environmental quality. The analysis revealed that with a 1% increase in the green index, environmental quality escalated by approximately 1.861%. Therefore, ecological quality will improve as a green index, such as green energy, green tax, and green innovation in the country. Green energy is environmentally friendly, while a green tax lowers carbon emissions, and green innovation is the implication of environmentally friendly production methods. Therefore, these findings indicate that the green index positively affects the environment. These results are consistent with those reported by Wang (2021).

While institutional quality is a crucial factor in attaining and maintaining a sustainable environment because of the grip of institutions on the economy, laws will be more precise and strictly implemented. All sectors, including industry, services, and manufacturing, consider state laws to preserve the environment. That is why strong institutions introduced and strictly implemented a green tax and green innovation to attain zero carbon. However, the findings reveal that a 1% increase in the IQ of the country's environment will improve it by 0.148%, indicating that IQ positively and significantly affects the environment. Good institutional quality incorporates the independence and impartiality of regulatory agencies, the clarity and consistency of environmental regulations, transparency, and accountability in implementing environmental policies. These findings were consistent with those reported by Piabuo et al. (2021).

Further, advancements in the digital economy assist in lowering carbon emissions because of the development of renewable energy sources, such as wind and solar power, which reduces the dependence on fossil fuels and greenhouse gas emissions. The findings show that with a 1% increase in the digital economy, environmental quality increases by 0.286%. These results were consistent with those reported by Haini (2021). Therefore, it is essential to consider the potential environmental impacts of technological innovations and regulate and encourage innovations that positively impact the environment. With the proliferation of new technologies and the Internet, the digital economy has experienced significant growth in recent years. This has created a new paradigm in how we conduct business, with digital platforms and tools enabling companies to operate more efficiently and effectively. However, this growth has raised concerns regarding the environmental impact of the digital economy. The digital economy has a significant carbon footprint. The energy required to power data centers, servers, and other digital infrastructure is substantial and is projected to increase as the demand for digital services increases.

Furthermore, producing and disposing of electronic devices and other digital products can have a significant environmental impact. There is a growing focus on promoting sustainability in the digital economy to address these concerns. It also involves promoting sustainable consumption patterns, such as encouraging the repair and reuse of electronic devices and promoting more sustainable business models.

Sustainable economic development and a healthy environment are interdependent, as one cannot exist without another. To ensure sustainable economic growth while preserving the environment, it is essential to implement measures such as investing in green technology and clean energy, promoting efficiency and waste reduction, conserving and managing biodiversity and ecosystems, encouraging sustainable tourism and agriculture practices, and implementing regulations and taxes to incentivize environmentally friendly business practices. The goal is to balance economic growth and environmental protection so that future generations can enjoy the benefits of economic progress without sacrificing environmental health. These results are consistent with those reported by Awodumi and Adewuyi (2020).

Moreover, natural resource rent is significantly associated with environmental quality because it refers to the income generated from extracting and selling natural resources such as oil, gas, minerals, and forests. Therefore, unregulated or poorly regulated natural resource extraction results in environmental degradation, pollution, and resource depletion. Thus, managing natural resource rent sustainability is essential when considering the potential ecological impacts. The findings reveal that the extraction of natural resources negatively influences environmental quality. The estimation shows that, with a 1% increase in natural resource rents, ecological quality declines by 0.050%. These findings were reinforced by Shen et al. (2021).

The institutional quality and green index (gnn*iq) creates an excellent environmental protection and sustainable development environment. By improving institutional quality and raising its ranking on a green index, a country can increase its efforts to preserve and enhance its environmental quality. The estimation suggests that the interaction term (gnn*iq) cumulatively influences ecological quality. This finding indicates that a weak and irregular (gnn*iq) negatively affects environmental quality. These results were consistent with those reported by Li et al. (2021).

5.1 Theoretical Contribution of the Study

Based on the empirical outcomes, it appears that the study confirms the principles of the Socio-Technical Systems Theory. Results highlight how digital evolution (technology usage), green initiatives (green taxes, green energy, and green innovation), and institutional quality (government effectiveness and political stability) collectively contribute to improved environmental sustainability in BRICS nations. This aligns with the theory, which posits that the interplay between technological advancements and institutional frameworks drives outcomes in socio-technical systems. Secondly, the positive and significant impact of a 1% increase in technology usage, improving environmental quality by 0.2867%, as well as the improvement in environmental quality due to green initiatives and institutional quality, confirms the theory's assertion that socio-technical systems can achieve favorable sustainability outcomes through their interaction. Third, the theory emphasizes the role of institutions in shaping the success of technical and social changes. Study findings that institutional quality, despite some negative short-term effects, has a long-term positive impact on environmental sustainability reflect the importance of strong institutional frameworks in guiding socio-technical changes. Lastly, the theory also supports the idea that innovation (here, green technologies) spreads through technical and social systems and drives changes in system performance. The significant effect of green innovation on BRICS nations' environmental quality, as seen in the study supports this. Thus, our empirical findings are consistent with the core principles of Socio-Technical Systems Theory, as they confirm the interconnectedness of technology, green initiatives, and institutional quality in driving sustainable development outcomes in the context of BRICS countries.

6 Conclusion

Globally, environmental quality is deteriorating owing to the significant contribution of hazardous gases and human activity, which results in climate change, rising temperatures, and ecological degradation. These changes can lead to more frequent and intense natural disasters, such as hurricanes and heat waves, and negative impacts on ecosystems, including loss of biodiversity and decreased crop yields. Additionally, carbon emissions contribute to air pollution, which causes respiratory and cardiovascular problems in humans. Therefore, technological innovation, the green index, natural resources, sustainable economic growth, institutional quality, and the interaction term green index plus institutional quality are employed to measure the influence on the environment to attain zero carbon. For this objective, a panel dataset of BRICS economies consisting of 1990–2021 was collected from world development indicators, ecological footprint, and ICRG.

The findings revealed that all the factors achieved zero carbon emissions in the BRICS economies. These aspects have a long-term affiliation with the environment and contribute to achieving zero carbon emissions. Therefore, the Q-regression approach was employed to measure the influence of these factors on the climate in quantiles.

This finding reveals that the green index has a significant positive association with the environment and assists in attaining zero carbon in BRICS economies. Furthermore, institutional quality is crucial in achieving zero carbon because strong institutional quality strictly implements laws and green taxes to attain environmental sustainability. Technological innovation, on the contrary, has a positive affiliation with environmental quality because economies are installing new technologies that cause zero or less harm to the environment. Moreover, the interaction term (gnn*iq) reveals that economies implementing green indices with a solid institutional hold positively influence the environment because weak adoption of green indices and poor institutional quality resist improving the environment.

6.1 Applicability of Findings and Policy Implications

The study's findings apply to policymakers and practitioners in BRICS nations and other emerging economies facing similar challenges. The research offers actionable insights for designing policies that leverage digital technologies and strengthen institutional frameworks to achieve sustainable development goals. Enhancing institutional quality is paramount for the successful implementation of environmental policies and the maximization of digitalization benefits. Policies aimed at improving governance, transparency, and regulatory enforcement can significantly amplify the positive impact of digitalization on sustainability. Secondly, governments should prioritize green innovation and adopt environmentally friendly technologies. Investing in research and development, providing incentives for renewable energy, and promoting sustainable industrial practices are essential for reducing environmental degradation while supporting economic growth. Lastly, the study highlights the importance of balancing economic growth with environmental sustainability. Policymakers must ensure that growth strategies align with environmental goals, particularly in rapidly industrializing economies like the BRICS nations.

6.2 Study Limitations and Future Directions

While this study offers valuable insights as the focus is on BRICS nations, it also provides depth and limits the generalizability of the findings to other regions or groups of countries with different socio-economic and environmental contexts. Future studies could expand the geographic scope to include a broader range of emerging and developed economies. The study utilizes data from 1990 to 2021, which may not capture the most recent technological advancements or policy shifts. Including more recent data in future research could provide a more up-to-date analysis of the evolving relationship between digitalization and environmental sustainability. Furthermore, although advanced econometric methods were used, there is always a risk of model specification errors, such as omitted variables or potential endogeneity, which could bias the results. Future research could address these issues by employing alternative models or more sophisticated techniques like Instrumental Variables (IV) or Difference-in-Differences (DiD). Thus, building on the findings of this study, future research could explore several avenues, such as expanding the analysis to include a broader set of countries, both developed and developing, to compare how digitalization and institutional quality affect sustainability across different contexts. Similarly, incorporating new indicators, such as social sustainability metrics or broader environmental indicators like biodiversity, could provide a more holistic view of sustainable development in emerging economies. Finally, future studies can consider sectoral analysis or longitudinal studies as well.

Data Availability Data will be made available on request.

Declarations

Conflict of interest The authors declare that they have no competing interests.

Consent for Publication The authors are willing to permit the Journal to publish the article.

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