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RESEARCH ARTICLE

Assessing the Impact of AI Innovation, Financial Development, and the Digital Economy on Load Capacity Factor in the BRICS Region

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Abstract

This study explores the impact of AI innovation, financial development, and the digital economy on the Load Capacity Factor (LCF) in BRICS nations from 2000 to 2019. Cross-sectional dependence and slope homogeneity tests reveal that the variables exhibit both dependence and heterogeneity. Panel unit root tests confirm stationarity, and a cointegration analysis establishes long-term relationships among the variables. The Panel ARDL method identifies a U-shaped relationship between income and LCF, supporting the LCC hypothesis. AI innovation and the digital economy positively influence LCF, promoting environmental sustainability. Conversely, financial development significantly reduces the LCF in both the short and long terms. To validate these findings, robustness checks using DKSE (Driscoll Kraay Standard Error), AMG (Augmented Mean Group), and CCEMG (Common Correlated Effects Mean Group) estimation techniques yield consistent results with the Panel ARDL analysis. Furthermore, the D-H causality test reveals unidirectional causal relationships from income, financial development, and the digital economy to LCF. It also identifies a bidirectional causal relationship between LCF and AI innovation. These findings highlight the dual role of AI and the digital economy in enhancing environmental sustainability while addressing the challenges posed by financial development in the BRICS nations.

Keywords: AI Innovation; Financial Development; Digital Economy; LCC Hypothesis; BRICS

Introduction

A growing emphasis on sustainable growth can be credited to the decline in the environment caused by corporate operations, industrialization, and the utilization of fossil fuels for energy (Dong et al., 2024). Since the SDGs were endorsed by the UN in 2015, nations in transition have faced numerous obstacles in accomplishing the objectives placed by the organization (Feng et al., 2024). To combat global ecological issues, the UN has designated "green energy" as the 7 sustainable development objectives (Chen,2022). Moreover, to keep temperature level to 1.5°C, Beck and Mahony (2018) predict that GHG emissions must be reduced by 45% until 2030 compared to 2010 levels, achieving net-zero status around 2050. A recent IPCC estimate states that by 2029, energy-related CO_2 emissions should rise by 40%–107% (Liu et al., 2023).We made use of the BRICS emerging economies to illustrate the need for appropriate resilience policies based on frameworks that take the link between the natural world, technological advances, and financial stability into consideration. We selected BRICS area for our empirical investigation concerning multiple scenarios. This countries are among the rapidly emerging nations that seek economic progress through misuse of resources, which exacerbates ecological degradation (Mahalik et al.,2024; Ahmad et al.,2024b). In 2020, the economy accounted for 23.5% of the world's total (Jafari et al. 2022). This development paradigm will deplete energy supplies, degrade the state of the economy, and increase the release of GHG's (Ameyaw et al. 2019; Nepal et al. 2021). As a result, they have pledged to reduce carbon emissions and broaden their energy investments, especially by adding renewable energies to their conventional power holdings (Ullah et al. 2023), to minimize global warming (Hassan et al. 2020). Regrettably, especially in emerging economies like the BRICS, economic expansion frequently takes priority over resilience and ecological health (Ghosh et al., 2023; Caglar et al., 2022). The LCF is a measure of ecological condition, is determined by calculating biocapacity from the EFP (Raihan et al., 2023b).

In the long run, GDP growth promotes the adoption of green technology, which lowers EF and improves LCF, even though it may initially hinder biocapacity (Voumik et al., 2024). The BRICS nations concentrate about 25% of the world's surface area, 40% of its population, and 25% of its economy. The contribution of BRICS to worldwide financial expansion has exceeded 40%. Forecasts commonly predict that BRICS will maintain its position as a major global power until 2050 (Tutar et al., 2024). Renewable energy technology adoption and innovation can be accelerated by financial development, which provides the funding needed, risk reduction, and incentive for investment (Premeph,2023; Sohail et al.,2019). Development in monetary field might promote advances in technology and cause the use of energy to fall, both of which could cut CO_2 (Ridwan, 2023; Onwe et al.,2024). However, the depletion of ecosystems and an upsurge in CO_2 can also be attributed to the expansion of the finance industry (Mngumi et al., 2024). The correlation between financial development (FD) and pollution is of utmost importance when pursuing responsible prosperity, especially in the economies of the BRICS countries. These nations are challenged by balancing their rapid growth with the increasing energy demands (Yadav et al., 2024; Faruk et al.,2023). Moreover, few works illustrated that the digital economy (DGE), symbolized by digital financial services, could present a previously rare chance to discover a resolution. Zhou et al. (2022) argue that it is possible to advance the decarbonization process without jeopardizing economic expansion or the well-being of individuals. Moreover, effective financial management stimulates the digital economy, environmental efforts, and a drop in CO_2 emissions from companies (Zhang et al., 2023; Sohail et al.,2018a). By utilizing cutting-edge technologies like Big Data and the Internet of Things, DGE can maximize the use of resources and achieve swift economic growth without compromising the environment (Baloch et al., 2024). Growing DGE is a good way to increase ecological efficiency, reduce resource and environmental strain, and raise national GDPs (Qin et al., 2022). AI has the potential to be a strong tool to boost productivity, efficiency, and imaginative thinking due to its potential for use in areas including robotics, data processing, and decision-making (Makridakis, 2017). Furthermore, artificial intelligence (AI), in particular machine learning models, are growing in popularity for optimizing systems in some fields, most notably CO_2 collection and emission reduction from human actions (Delanoe et al., 2023).

The EF measures the globe's capacity to replenish its resources and the amount of productive land required to replace the assets consumed by global populations (Sonu et al., 2011). However, prior studies have not sufficiently explored the supply side of the ecology. According to Sieche et al. (2010), a value of "1" signals the sustainability threshold, but results below "1" indicate the current ecological condition is unsustainable. These reasons make it clear that the LCF is a better indicator than CO_2 emissions and EFP because it shows the supply and demand of ecological resources (Pata and Balsalobre-Lorente, 2022). This study's goal is to examine, utilizing data from 1980 to 2017, how the digital economy, financial development, economic growth, and AI innovation affect the LCF. It achieves this by combining the ARDL approach with the LCC hypothesis. The following are the research's main adds to the ecological literature: (i) this is the first attempt to investigate how AI innovation and the digital economy affect LCF in the context of rising economies, particularly those of the BRICS nations. (ii) A few studies have used LCF as a metric to examine how financial development affects environmental damage. (iii) Within the context of the BRICS, this research explores the practicality of the Load Capacity Curve (LCC) theory. (iv) Our work made use of innovative techniques such as DKSE, AMG, and CCEMG, along with the D-H causality test, to establish causal relationships between the LCC hypothesis and its determinants, ensuring its robustness. The major findings of the study show that GDP squared, AI innovation, and the DGE have a positive impact on the ecosystem in the BRICS region, whereas GDP growth and financial expansion lead to ecosystem unsustainability. Therefore, policymakers can use these findings to support green growth, implement AI, and foster sustainable monetary growth within and outside of the BRICS community.

The interplay of AI, financial development, and the digital economy is crucial in advancing global sustainability goals, particularly the United Nations Sustainable Development Goals (SDGs). AI, with its ability to analyze complex data, optimize resource use, and enhance efficiency, plays a pivotal role in supporting sustainable industrialization (SDG 9) by streamlining manufacturing processes and reducing waste. Financial development, on the other hand, provides the necessary investment and resources to foster innovation and infrastructure, enabling industries to adopt cleaner and more sustainable technologies. The digital economy accelerates these advancements by connecting stakeholders, facilitating access to markets, and enabling the widespread adoption of green technologies. Together, these factors also drive progress in climate action (SDG 13) by improving predictive analytics for environmental changes, promoting green financing for climate projects, and enabling the shift toward low-carbon industries. Moreover, they support affordable and clean energy (SDG 7) by enhancing energy management systems, improving renewable energy integration, and expanding access to clean energy technologies in underserved regions.

There are five sections in this analysis. The second part, which follows the introduction, is a review of the literature that spotlights specific results and brings up areas for additional study. The third section describes the research variables, methods, and data sources. The fourth segment offers a comprehensive evaluation and discussion of the outcomes. The sixth and seventh sections, respectively, provide the conclusions and policy implications.

Literature Review

Numerous scholarly investigations explore the complex links between financial development, technical innovation, economic growth, and LCF across various geographic contexts. Furthermore, after thoroughly analyzing the corpus of prior research and providing new insights into the intricate relationships between creative variables, such as AI innovation and the digital economy. Our goal in going beyond conventional evaluation is to bring a unique perspective to this quickly evolving field of research.Multiple investigations in the body of literature have analyzed the link between monetary development and ecological systems, each using separate methods and in different areas; they discovered varying degrees of accomplishment. From 1992 to 2020, Gu et al. (2024) focused on how economic expansion altered the BRICST economies' EFP. Using found that there is a link between GDP rise and a spike in ecological difficulties by utilizing the DOLS, FE-OLS, and MMQR methodologies. Latif et al. (2023) investigated how GDP affected LCF in 48 Asian nations between 1996 and

2020. The analysis revealed that environmental damage is caused by GDP growth. Similarly, Pattak et al. (2023) considered Italy adopting the STIRPAT and ARDL framework from 1972 to 2021. The analysis deployed that an additional 1% in GDP causes 8.08% spike in CO2 pollutions. From 1990 to 2018, Yang et al. (2023) evaluate the LCC hypothesis's applicability using the MMQR technique. They demonstrate that GDP has detrimental consequences on ecological quality. A substantial amount of research also found similar outcomes, such as Voumik et al. (2023b) in Kenya; Hassan et al. (2024) in BRIC countries; Raihan et al. (2023c) in Malaysia; and Ridwan et al. (2023) in France. However, Raihan et al. (2024a) used the ARDL model to conduct a study and discovered that economic growth was somewhat responsible for India's emissions reduction. Similar to this, Raihan et al. (2023a) observed that rising GDP growth may eventually result in lower levels of emissions in China based on the PHH hypothesis. However, Muhammad et al. (2020) employed two-stage least squares regression techniques and found a U-shaped connection between GDP and emissions.

The impact of artificial intelligence (AI) innovation on low-carbon footprints (LCF) remains insufficiently understood. Some researchers have highlighted the potential ecological consequences of AI as relevant studies continue to emerge (Al-Sharafi et al., 2023; Ridwan et al., 2024e; Rahman et al., 2024). With the advancement of digital technologies, the rising demand for energy intensifies environmental degradation, as noted in various studies. Industrial digitalization has led to increased energy consumption and exacerbated environmental harm compared to historical levels (Li et al., 2020; Ridzuan et al., 2023; Hossain et al., 2023; Sohail et al., 2018b; Shiam et al., 2024a). On a positive note, advancements in technology have been found to enhance China's ecological conditions (Raihan et al., 2022a). Alpan et al. (2022) and Arif et al. (2024) observed that AI's capabilities in learning, relationship-building, and decision-making for specific contexts, when combined with the effective integration of the Internet of Things (IoT), could accelerate efforts to reduce CO2 emissions. Wang et al. (2023) assessed AI's global impact on ecological footprints from 2010 to 2019, concluding that AI significantly reduces ecological footprints and advocating for increased government investment in AI research and deployment. Conversely, Liang et al. (2022), using data from China and an interactive three-stage network DEA model, found that the manufacturing sector has substantial room for improvement in leveraging AI to reduce pollutants. Additional research by Chan and Huang (2003), Rasheed et al. (2024), Rana et al. (2023), Ferdous et al. (2023), and Masood and Ahmad (2021) has further suggested that AI innovation contributes to ecological sustainability.

Several researchers have examined the influence of financial development (FD) on the advancement of a sustainable ecology. Scholars argue that FD benefits the ecosystem by attracting foreign investment (Eskeland and Harrison 2003; Raihan et al.,2024h; Islam et al.,2023), promoting the adoption of greener technologies (Frankel and Rose 2002; Tanchangya et al.,2024), and providing low-interest funding for ecologically sound projects (Tamazian and Rao 2010; Shiam et al.,2024b). All of these factors help to create more sustainable and clean surroundings. Rahman et al. (2023) examine the implications of FD on the environment in the BRICS countries. The study used FMOLS and DOLS panel estimation techniques, and it found that financial development significantly increases environmental sustainability. Similarly, financial development also improves natural health in the member states of the Asia-Pacific Economic Cooperation by reducing CO2 pollution (Zafar et al., 2021). Conversely, from 1990 to 2018, Li et al. (2024) explored how the BRICS economies' financial expansion affected ecological well-being. Using the CS-ARDL approach, they discovered that FD harms environmental quality. According to Saqib et al. (2024), financial development degrades environmental quality. They examined the effects of these developments on the environment and equitable development in the ten countries with the highest EF. Ali et al. (2023) used several techniques, including OLS, PQR, and CCEMG, and found comparable results, indicating that financial development was the cause of biodiversity loss in the E-7 region. However, Zhao et al. (2021) discovered unexpected results, indicating that FD has a direct and probably mild impact on ecological damage. This further emphasizes the fact that financial inclusion has distinct effects on emissions.

According to Kuntsman and Rattle (2019), the development, upkeep, and disposal of digital equipment have all harmed the environment. By connecting all aspects of business over the Internet, Moriset and Malecki (2009) contend that the DGE reduces physical location. An increasing body of research (Wang et al., 2021; Ma et al., 2022) has examined how the digitalized economy affects CO2 emissions; nevertheless, there exits deficiency of analysis comparing DGE and LCF. Raihan et al. (2024c) examine the effect of the DGE on CO2 emissions in the G-7 region between 1990 and 2019. The paper utilized the ARDL model, revealing a significant mitigation in carbon footprint due to the digital economy. In a similar vein, Jiang et al. (2024) found that in 30 Chinese regions, carbon emissions decrease by 0.082–0.092% for a 1% surge in the DGE. The use of spatial econometric approaches achieved this. Moreover, researchers have found that the improvement of the DGE also reduces the emissions of the closest provinces. Li et al. (2023) apply the ARDL technique to explain how the next eleven economies enhanced their LCF between 1990 and 2018. Over time, the results show that reliance on DGE reduces LCF. On the other hand, Xu et al. (2024) report that the relationship between CO2 emissions and the digital economy is inverted U-shaped, with the effects of quality of life on CO2 emissions decreasing as the DGE progresses. Furthermore, Li et al. (2021) recommend hedging practices to mitigate early-stage CO2 emissions associated with the DGE.

Despite the existence of analyses on the association among GDP, financial development, urbanization, and ecological damage, there is still a need for further research in this field, particularly in the BRICS countries. Furthermore, less research has been done on how AI innovation and the digital economy impact LCF, particularly in the selected area. To bridge such gaps, this research investigates the associations between the BRICS region's GDP, DGE, AI innovation, FDI, and LCF. By examining these neglected areas, the analysis provides a fresh viewpoint on the complex processes influencing the ecosystem level in those targeted areas. The study adds a tremendous deal of value to the field by offering insights that stakeholders and policymakers dealing with ecological concerns in the bloc of BRICS nations require.

Methodology

Data and Variables

This work used data to explore the implications of several independent variables on the LCF of the BRICS countries between 1990 and 2019. We collected the LCF as a dependent factor from the reliable Global Footprint Network (GFN) for this analysis. We gather information about the digital economy, AI innovation, and financial development from WDI, Our World in Data, and the IMF, which aligns with the policy variable in our research. Furthermore, the WDI provides information about the GDP variable. A key component of the study is Table 1, which offers a full description of all of the factors examined along with helpful information regarding their background, definitions, and units of measurement.

Theoretical Framework

We utilized the LCC hypothesis, which claims that there prevails a U-shaped link between GDP and environmental condition (Pata & Kartal, 2023). This connection underscores the importance of understanding how resource consumption rises in tandem with GDP growth and increases in individual assets, highlighting it as a critical element of ecological sustainability (Degirmenci & Aydin, 2022). Several research studies, including (Huang et al., 2023; Atasoy et al.,2022a; Shahzad et al., 2024; Islam et al.,2024; Hossain et al.,2024; Ridwan et al.,2024d), used the LCF as an endogenous factor in their analysis. We include AI innovation as a new component in our analysis in addition to financial development as examined by Destek and Sarkodie (2019). We also take into account the digital economy, which Zhang et al. (2022) have identified as a major environmental driver.

Table 1. Source and Description of Variables

Variables	Description	Logarithmic Form	Unit of Measurement	Source
LCF	Load Capacity Factor	LLCF	Gha per person	GFN
GDP	Gross Domestic Product	LGDP	GDP per capita (current US$)	WDI
AI	AI Innovation	LAI	Annual patent applications related to AI	Our World in Data
FD	Financial Development	LFD	Financial Development Index	IMF
DGE	Digital Economy	LDGE	Imports of ICT goods (% of total imports)	WDI

In our current analysis, we have created the following equation (1) for LCC theory:

$$Load\ Capacity\ Factor = f(GDP, GDP^2, Z_t) \quad (1)$$

Here, the variables for income in equation (1) are GDP and GDP squared, while the variable for additional factors impacting the LCF is Zt. The purpose of incorporating more noteworthy factors such as financial development, digital economy, and innovation into AI Equation (2) is to enhance the understanding of the aspects that impact the LCF.

$$LCF = f(GDP, GDP^2, AI, FD, DGE) \quad (2)$$

In equation (2) innovation in AI is denoted by AI, development in finances is symbolized by FD, and digital economy is represented by DGE. Equation (3) is used for economic modification:

$$LCF_{it} = \alpha_0 + \alpha_1 GDP_{it} + \alpha_2 GDP_{it}^2 + \alpha_3 AI_{it} + \alpha_4 FD_{it} + \alpha_5 DGE_{it} \quad (3)$$

The logarithmic values of the variables are shown in equation (4). It simplifies complex relationships into simpler linear forms, which improves understanding and makes it possible to draw conclusions based on statistics.

$$LLCF_{it} = \alpha_0 + \alpha_1 LGDP_{it} + \alpha_2 LGDP_{it}^2 + \alpha_3 LAI_{it} + \alpha_4 LFD_{it} + \alpha_5 LDGE_{it} \quad (4)$$

Empirical Methodology

This inquiry's evaluation process is divided into seven stages. We initially utilize the Pesaran CSD test to gauge the dependencies across the countries. We then implement the slope homogeneity test. Third, we employ the first and second-generation unit root analyses (IPS, CIPS, and CADF) to confirm stationarity. The panel cointegration evaluation is the fourth step. We implement the ARDL framework in the fifth step to determine both short-term and long-term associations. Then, we conducted the DKSE, AMG, and CCEMG to verify the consistency of the long-run estimation. Ultimately, we performed the D-H causality examination to measure the correlation between the chosen parameters.

CSD Test

To assure the validity of estimates and the accuracy of conclusions, it is imperative that we tackle the CSD difficulty (Grossman and Krueger, 1991). The incidence of CSD is due to various factors, such as externalities, implicit variation, economic and geographical interaction, and unseen correlated variables. To solve this problem, we used a CSD assessment proposed by Pesaran (2004). For this particular situation, the equation below is applicable:

$$\mathrm{CSD} = \sqrt{\frac{2}{\mathrm{N(N-1)}}}\left(\sum_{\mathrm{i=1}}^{\mathrm{N-1}}\sum_{\mathrm{j=i+1}}^{\mathrm{N}}\sqrt{\mathrm{T_{ij}}}\ \hat{\rho}_{\mathrm{ij}}\right) \tag{5}$$

Slope Homogeneity Test

When analyzing panel data, we must address slope heterogeneity due to the variation in weight across different countries. We utilized Pesaran and Yamagata (2008), SH testing in this investigation. We applied the following equations to the SH test:

$$\breve{\Delta} = \sqrt{N\left(\frac{N^{-1}S\% - k}{\sqrt{2k}}\right)} \text{ and } \breve{\Delta}_{adj} = \sqrt{N\left(\frac{N^{-1}S\% - k}{\sqrt{\frac{2k(T-k-1)}{T+1}}}\right)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(6)$$

Panel Unit Root Test

Our initial investigation deployed the first generation IPS test developed by Im et al. (2003). Then, we used Pesaran's CIPS and CADF, which are second-generation unit root analyses that take into account slope heterogeneity and CSD. The purpose of these examinations was to validate the efficacy of ARDL as a substitute for typical cointegration methods. Equation (7) marks the results of the IPS test.

$$\Delta y_{it} = \delta_i + \alpha_i t + \beta y_{it-1} + \rho_i \Delta y_{it-1} + \varepsilon_{it} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (7)$$

The CIPS test equation takes the following form:

$$CIPS = \frac{1}{N}\sum_{i=1}^{N} t_i\,(N,T)\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(8)}$$

Here 'N' represents a cross-sectional dimension, and 'T' represents a time series dimension. The CADF method is presented by equation (9):

$$\Delta Y_{it} = \beta_i + \rho_i Y_{i,t-1} + \vartheta_i \bar{Y}_{t-1} + \sum_{j=1}^{p} \gamma_{ij} \Delta Y_{i,t-1} + \varepsilon_{it} \ldots\ldots\ldots\ldots \text{(9)}$$

Where, $\bar{Y}_{t-1}$ and $\Delta Y_{i,t-1}$ are average for lagged and first difference of each cross-sectional series.

Panel Cointegration Test

This work measured panel cointegration using a second-generation method created by Westerlund (2007). This method provides consistent and dependable results even when CSD is present (Kapetanios et al., 2011). The conventional structure of this test is illustrated by the following four equations:

$$G_a = \frac{1}{n}\sum_{i=1}^{N} \frac{\acute{a}_i}{SE(\acute{a}_i)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(10)}$$

$$G_t = \frac{1}{n}\sum_{i=1}^{N} \frac{T\acute{a}_i}{a_i(\acute{1})} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(11)}$$

$$P_t = \frac{\acute{a}}{SE(\acute{a})} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(12)}$$

$$P_a = T\acute{a} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(13)}$$

Here, mean group statistics are indicated by Gt and Ga, and cointegration is symbolized by Pt and Pa.

Panel ARDL Model

This study utilizes the ARDL technique, first introduced by Pesaran et al. (2001), as an efficient method to assess the short- and long-term connection among the model's factors. It can outperform the OLS, VECM, and VAR models in both term estimations as a result of its independent latency length framework (Voumik and Ridwan, 2023). Furthermore, by accounted for the delayed period of variables, we can implement this model to investigate endogeneity (Voumik et al., 2023c; Polcyn et al.2023). Unlike the traditional approach, this model enables the researcher to use a variety of variables with various lag times (Hasan et al., 2023; Voumik et al.,2023a). Researchers can separately investigate the long- and short-run period of this method (Rehman et al., 2021; Ridwan & Hossain, 2024). Equation (14) displays the ARDL long-run estimation.

$$\begin{aligned} lnLCF_t = {} & \partial_0 + \partial_1 \mathrm{lnLCF_{t-1}} + \partial_2 lnGDP_{t-1} + \partial_3 lnGDP^2{}_{t-1} + \partial_4 lnAI_{t-1} + \partial_4 lnFD_{t-1} + \partial_7 lnDGE_{t-1} \\ & + \sum_{i=1}^{w} \vartheta_1\, \Delta lnLCF_{\mathrm{t-i}} + \sum_{i=1}^{w} \vartheta_2\, \Delta \mathrm{lnGDP_{t-i}} + \sum_{i=1}^{w} \vartheta_3 \Delta lnGDP^2{}_{t-1} + \sum_{i=1}^{w} \vartheta_4\, \Delta\, lnAI_{t-i} \\ & + \sum_{i=1}^{w} \vartheta_5 \Delta \mathrm{lnFD_{t-i}} + \sum_{i=1}^{w} \vartheta_6 \Delta \mathrm{lnDGE_{t-i}} + \epsilon_t \qquad \text{(11)} \end{aligned}$$

We compare the information supporting cointegration to the null hypothesis, which suggests the absence of cointegration. If the F-statistic exceeds both the lower and upper limits values, the null hypothesis is rejected. The following two possibilities are presented:

$$H_0 = \vartheta_1 = \vartheta_2 = \vartheta_3 = \vartheta_4 = \vartheta_5 = \vartheta_6 \tag{15}$$

$$H_1 = \vartheta_1 \neq \vartheta_2 \neq \vartheta_3 \neq \vartheta_4 \neq \vartheta_5 \neq \vartheta_6 \tag{16}$$

Our research adopts the ECM model (Engle & Granger, 1987) to analyze both short- and long-term connections. Equation (17) reveals the short-term link by utilizing the ARDL estimates.

$$lnLCF_t = \vartheta_0 + \sum_{i=1}^{w} \vartheta_1 \Delta \mathrm{lnLCF_{t-i}} + \sum_{i=1}^{w} \vartheta_2 \Delta \mathrm{lnGDP_{t-i}} + \sum_{i=1}^{w} \vartheta_3 \Delta \mathrm{ln}GDP^2{}_{\mathrm{t-i}} + \sum_{i=1}^{w} \vartheta_4 \Delta\, lnAI_{t-i} + \sum_{i=1}^{w} \vartheta_5 \Delta \mathrm{lnFD_{t-i}} + \sum_{i=1}^{w} \vartheta_6 \Delta \mathrm{lnDGE_{t-i}} + \ell ECT_{t-i} + \in_t \tag{17}$$

Robustness Check

We utilized the Driscoll and Kraay (1998) developed DKSE test, a commonly used method for addressing CSD. Unlike traditional standard errors, DKSE reduces the risk of biases and errors during parameter estimation by accounting for potential correlated data errors (Ridwan et al., 2024a). Alternatively, we can establish CDs using the highly resilient AMG estimator (Eberhardt and Bond 2009). In the end, we used Pesaran (2006) CCEMG, which can handle structural cracks that can't be seen and common features that don't stay in place (Kapetianos et al., 2011).

D-H causality Test

This work used the causality method (Dumitrescu & Hurlin, 2012) to illustrate the causal relationship between the variables. We prefer this test over the panel Granger causality test because it incorporates cross-sectional dependence. This technique allows for the estimate of both N > T and T > N samples, which gives it plenty of versatility and is useful for providing consistent findings during CD (Ahmed and Le, 2021). We can express the D-H panel's causality as follows:

$$\mathrm{y_{it}} = \theta_\mathrm{i} + \sum_{\mathrm{j-1}}^{\mathrm{j}} \lambda_\mathrm{i}^\mathrm{j} \mathrm{y_{i(t-j)}} + \sum_{\mathrm{j-1}}^{\mathrm{j}} \beta_\mathrm{i}^\mathrm{j} \mathrm{x_{i(t-j)}} + \varepsilon_\mathrm{it} \tag{14}$$

Results and Discussion

Table 2 is the descriptive statistics, which is the first step towards examining variables and fully grasping their properties, including mean, standard deviation, minimum and maximum values, etc. Out of all the variables, LGDP2 has the greatest mean (76.62), whereas LFD has the lowest mean. While LLCF has the lowest value, LGDP2 also has the largest value. Moreover, positive skewness in LLCF and LDGE indicates a concentration of values to the right of the mean, while negative skewness in LGDP, LGDP2, LAI, LRSP, and LFD indicates a leftward skew. In these distributions, all variables, except LGDP and LGDP2, have kurtosis values less than 3, indicating modest platykurticity. The findings of the Jarque-Bera test show that none of the parameter data sets had a normal distribution.

Table 2. Summary statistics of variables

Statistic	LLCF	LGDP	LGDP2	LAI	LFD	LDGE
Mean	-0.099205	8.744605	76.6202	3.054113	-0.508423	2.303808
Median	-0.170368	8.808211	77.5848	3.113269	-0.507575	2.165588
Maximum	1.972074	9.22577	85.11483	3.89182	-0.226608	3.260742
Minimum	-1.562449	7.693433	59.18891	1.791759	-0.950286	1.302204
Std. Dev.	1.055331	0.391927	6.688636	0.500842	0.214967	0.451703
Skewness	0.12615	-1.100278	-1.010352	-0.405564	-0.200829	0.691474
Kurtosis	1.644066	3.526287	3.32096	2.437028	1.657579	2.807014
Jarque-Bera	7.925885	21.33094	17.44276	4.061935	8.180928	8.124125
Probability	0.019007	0.000023	0.000163	0.131209	0.016731	0.017213
Sum	-9.920473	874.4605	7662.02	305.4113	-50.8423	230.3808
Sum Sq. Dev.	110.2586	15.20711	4429.048	24.83345	4.574878	20.1995
Observations	100	100	100	100	100	100

Table 3 demonstrates the Pesaran CSD test outcomes. The p value for all variables is 0.000, indicating that all CSD statistics values are highly significant at the 1% significance threshold. The null hypothesis, which posits that there is no CSD across nations, is denied for all of the factors, as shown by the results. This implies that a change in one of the sample countries may also affect the remaining nations.

Table 3. Cross sectional Dependence test

Variables	CD-Statistics	P-Value
LLCF	9.73***	0.000
LGDP	13.26***	0.000
$LGDP^2$	13.20***	0.000
LAI	5.63***	0.000
LFD	8.53***	0.000
LDGE	7.58***	0.000

The slope heterogeneity examination results in Table 4 demonstrate that the existence of slope heterogeneity is well-supported. Based on the P-values of 0.022 and 0.004, this implies the rejection of the null hypothesis that no slope heterogeneity exists.

Table 4. Results of SH test

SH tests	Δ statistic	P-value
$\tilde{\Delta}$ test	2.292**	0.022
$\tilde{\Delta}_{adj}$ test	2.843***	0.004

"Null Hypothesis: Slope of the coefficients are homogenous"

Table 05 illustrates the unit root evaluations' conclusions. The IPS test outcomes suggest that all other variables become stationary after the initial difference, keeping only LGDP and LGDP2 stationary at the level form. The CIPS and CADF assessments indicate that the remaining factors (LLCF, LAI, LFD, and LDGE) are stationary at I(1). Additionally, evaluations indicate that LGDP and LGDP2 are stationary at the I(0) level. In summary, the other elements are stationary in their level form I(0), while LLCF, LAI, LFD, and LDGE are stationary at the first difference I(1).

Table 5. Results of panel Unit root test

	IPS		CIPS		CADF		Decision
	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	
LLCF	-1.606	-4.704***	-1.635	-3.680***	-1.922	-3.630***	I(1)
LGDP	-3.045***	-4.256***	-3.180***	-4.570***	-3.174***	-4.890***	I(0)
$LGDP^2$	-3.031***	-4.381***	-3.105***	-4.089***	-3.012***	-4.075***	I(0)
LAI	-1.854	-7.130***	-1.107	-5.381***	-1.677	-5.022***	I(1)
LFD	-1.902	-5.465***	-1.184	-5.866***	-1.985	-4.091***	I(1)
LDGE	-2.054	-4.498***	-2.081	-4.814***	-1.067	-3.618***	I(1)

In Table 06, using four test statistics, the Westerlund (2007) cointegration test assesses long-term correlations between variables. P-values less than 0.05 for the Gt and Pt test statistic support the rejection of the null hypothesis. It indicates the presence of cointegration and a steady, long-term association between the factors in the panel dataset.

Table 6. Results of Panel Cointegration test

Statistics	G_t	G_a	P_t	P_a
Value	-4.821***	-5.680**	-4.231**	-3.413***
Z-Value	-1.891	1.975	2.671	1.407
P-Value	0.001	0.021	0.039	0.001

The Panel ARDL model's results, presented in Table 07, demonstrate the intricate dynamics influencing the BRICS region's carbon pollution. In terms of LGDP, the short-term coefficient is 0.3017 while the long-run coefficient is -0.4131, and both are statistically significant at conventional levels. This suggests that economic expansion alone contributes to environmental degradation in this setting. Our results support the encouraging link between GDP and environmental damages found by Alotaibi and Alajlan (2021), Raihan et al.(2024b), Kongkuah (2021), Raihan et al.(2022b), Rahman et al.(2022), Ahmad et al.(2024a) and Sun et al. (2024). However, this result defies previous observations made in West Africa (Halliru et al., 2020). Similarly, LGPR has a positive association with LCO2 in both periods. In the short run, the coefficient has a positive value of 0.0206, and in the long run, the value is 0.1362. The variable is significant because its p value is less than the conventional level for both periods. This conclusion highlights that long-term green growth cause's betterment for the natural world. Furthermore, there is a beneficial connection between AI innovation and LCF across both short and long periods. Specifically, a 1% expansion of LAI in the long and short term will boost LLCF by 0.0216% and in 0.040%. These results imply that utilization of modern AI technology could boost ecological conditions in both terms, and the results are significant in both terms. It aligns with the outcome of Raihan et al.(2024g), Atasoy et al.(2022a), Shiam et al.(2024c); Ridwan et al.(2024b), Ridwan et al.(2024c). For real-time hazardous material monitoring in-ground and plant matter, there are several benefits to utilizing AI-powered sensors and equipment (Singh and Kaur, 2022). The study by Pachot and Patissier (2022), Abir (2024), Mithun et al.(2023) and Yadav and Singh (2023) demonstrate the potential of AI to enhance ecological sustainability. Conversely, these destructive relations between LFD and LLCF persist in both the long and short term. In both the long and short term, an additional 1% increase in LFD is responsible for a fall of LLCF by 0.017% and 0.023%, respectively. This result is significant at conventional thresholds and indicates that financial development is not good for the BRICS region's ecosystem. However, because financial growth has a beneficial impact on CO2 pollutions, Al-Mulali et al. (2025) stated that it can improve ecosystem level both in the short and long term. The conclusions observed by Khan et al. (2021) in 184 nations and Yasin et al. (2021) in 59 less developed economies, Akther et al.(2024) in USA, Bala et al.(2024) in G-7 areas, Abir et al.(2024) within USA and Raihan et al.(2024d) within Indonesia are consistent with our analysis. In both the short and long term, the table demonstrates a positive relationship between LDGE and LLCF in both short and long terms. The long-term results indicate statistical significance with a p value of 0.015, while the short-term results demonstrate insignificance with a p value of 0.015 and the short-term results with a p value of 0.065. For every 1% increase in LDGE, there will be a 0.244% and 0.117% spike in LLCF in the long run and short run, respectively. In particular, the effect suggests that the digital economy raises the ecosystem's level. Our results concur with Dai et al. (2023) in emerging territories. However, Zhao et al. (2024) don't agree with us and claim that the digital economy harms the environment.

Table 7. Results of Panel ARDL model

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
Long-run Estimation				
LGDP	-0.744	0.5343	-4.7975	0.000
LGDP2	0.874	0.5380	4.8730	0.000
LAI	0.216	0.0381	5.6685	0.000
LFD	-0.017	0.1070	-5.1666	0.048
LDGE	0.244	0.0983	2.4839	0.015
Short-run Estimation				
COINTEQ01	-0.454	0.3233	-4.4051	0.005
D(LLCF(-1))	-0.108	0.3081	-4.3524	0.025
D(LGDP)	-0.226	0.2331	5.1260	0.000
D(LGDP2)	0.343	0.8553	-4.1255	0.000
D(LAI)	0.040	0.0310	6.3065	0.000
D(LFD)	-0.023	0.2622	-3.0903	0.028
D(LDGE)	0.117	0.2441	0.4797	0.065
C	10.494	2.6559	10.399	0.000

Table 8 uses three distinct estimating strategies to detect the validity of ARDL results. With values of -0.243 in DKSE, -0.781 in AMG, and -0.530 in CCEMG estimates, the predicted coefficients for LGDP reveal a negative connection with LCF across all approaches. The short- and long-term results of the ARDL model align with the negative influence of the LGDP variable on LCF in the BRICS zones, a finding that every scenario supports at the 1% significance level. Conversely, the encouraging connection between LLCF and LGDP2 suggests that sustained, substantial increases in GDP do not negatively impact the BRICS ecosystem. In the DKSE estimation, at the 1% level, in AMG, at the 5% level, and in CCEMG, at the 10% level, the LGDP2 variable is significant. In a similar vein, all approaches demonstrate favorable relationships between the LAI coefficient and LLCF. To be more specific, for every 1% improvement in AI innovation, the LLCF grows by 0.229% in the DKSE, 0.036% in the AMG, and 0.029% in the CCEMG. In DKSE, AMG, and CCEMG, the LAI factor is statistically significant at a level of 1%, supporting the conclusions of the ARDL model and emphasizing the beneficial effects of AI innovation on the ecological systems of the BRICS territories. All three analyses failed to identify any beneficial connection between LLCF and LFD. In DKSE, AMG, and CCEMG, the LFD coefficient is significant at the 1%, 5%, and 10% thresholds, consequently. According to these results, for every 1% increase in LFD, there is a corresponding decline in LLCF of 0.127%, 0.129%, and 0.516%. This suggests a connection between biodiversity loss and increased financial development in the BRICS region. Conversely, the upward trend between LDGE and LLCF confirms that more digitalized economy promotes biodiversity in the area under study. Across all estimations, the LDGE variable is significant at the 1% threshold. These results bolster the study's conclusions and the ARDL model, which served as the main estimating technique.

Table 8. Results of Robustness Check

VARIABLES	(1) DKSE	(2) AMG	(3) CCEMG
LGDP	-0.243***	-0.781***	-0.530
	(0.947)	(0.368)	(0.148)
LGDP2	0.650***	0.328**	0.691*
	(0.353)	(0.402)	(0.185)
LAI	0.229***	0.036***	0.029***
	(0.145)	(0.013)	(0.114)
LFD	-0.127***	-0.129**	-0.516*
	(0.360)	(0.0991)	(0.523)
LDGE	0.583***	0.073***	0.069**
	(0.0982)	(0.0991)	(0.206)
Constant	15.876***	12.575***	14.890***
	(4.845)	(6.283)	(4.680)
Observations	100	100	100
Number of groups	5	5	5
R-squared	0.977	0.891	0.985

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

Table 9 presents the outcomes of the D-H causality test. The analysis reveals a unidirectional causal connection between LLCF and LGDP, LGDP2, and LFD, as evidenced by the p-value of less than 0.05 for each instance.

This allows us to reject the null hypothesis that there exists no causal connection and establish that LGDP, LGDP2, and LFD are Granger causes of LLCF. Additionally, there is evidence that LAI and LLCF have a bidirectional causal relationship. However, we have not found any causal link between LDGE and LLCF, nor within LGDP2, LFD, or LDGE. Given that the corresponding p-values in these instances are greater than 0.05, we cannot reject the null hypothesis that there is no causality. As a result, it is possible to assert that neither LDGE nor LLCF are Granger-caused by one another.

Table 9. Results of D-H causality test

Null Hypothesis	W-Stat	Zbar-Stat	Prob.
LGDP ≠ LLCF	7.99979	4.43646	0.006
LLCF ≠ LGDP	2.60139	0.18715	0.851
LGDP2 ≠ LLCF	7.78583	4.26804	0.054
LLCF ≠ LGDP2	2.61761	0.19991	0.841
LAI ≠ LLCF	4.54821	1.71957	0.015
LLCF ≠ LAI	6.6585	3.38067	0.004
LFD ≠ LLCF	3.84299	1.16446	0.044
LLCF ≠ LFD	2.49106	0.1003	0.920
LDGE ≠ LLCF	2.55677	0.15203	0.079
LLCF ≠ LDGE	7.39168	3.95779	0.574

Conclusion and Policy Recommendation

The study looked closely at the complex links between GDP, financial development, AI innovation, and the digital economy on LCF in the BRICS nations between 1995 and 2022. Sophisticated econometric techniques analyzed the LCC hypothesis, identifying key factors affecting regional load capacity. This investigation verified that the dataset was free of unit root issues by performing analyses for CSD and slope homogeneity, as well as using both first- and second-generation unit root tests to address potential methodological challenges. Additional panel tests for cointegration highlighted the interrelated nature of the variables by demonstrating long-term interactions between them. The study employed the ARDL framework to capture the short- and long-term interactions among the selected factors. The ARDL findings revealed that, in the BRICS region, AI innovation, the squared GDP term, and the digital economy had encouraging consequences for LCF. Conversely, we found that both GDP growth and financial expansion had negatively impacted the ecosystem. We utilized techniques such as DKSE, AMG, and CCEMG to ensure the resilience of the conclusions. We also investigated the possible causal links between each variable using the Dumitrescu-Hurlin (D-H) causality test. Findings suggested a one-way causal association between LCF, FD, and GDP. Additionally, there was proof of a reciprocal causal relationship between LCF and AI innovation. However, we found no clear causal relationships between LCF and DGE, nor between LCF and GDP, FD, or GDP squared. Furthermore, this work emphasizes how crucial it is to give sustainable development proper consideration in finance and pursue balanced growth to mitigate its detrimental impact on biodiversity. Finally, it provides policymakers and stakeholders with meaningful knowledge and a comprehensive understanding of all factors affecting environment sustainability in BRICS area. The findings of this research carry substantial policy frameworks for the BRICS nations, particularly in the realms of monetary expansion, sustainable ecosystem, and advances in technology. Given the beneficial influence of AI innovation and the digital economy on the LCF, lawmakers might encourage the integration of advanced technologies into their economic frameworks to foster sustainable growth. Investment in AI and digital infrastructure could not only foster productivity but also contribute to green environment by optimizing resource usage and reducing carbon footprints. Conversely, the study's revelation that financial development lowers the LCF suggests that unregulated financial expansion might responsible for unsustainable resource use and environmental degradation. The U-shaped relationship between income and the LCF indicates that as economies grow, initial increases in income may strain environmental resources, but further growth, coupled with technological advancements, can reverse this trend. Thus, it is crucial for BRICS countries to focus on achieving balanced economic growth that leverages technological innovations to mitigate environmental impacts. Furthermore, the study's findings of causal relationships suggest that targeted interventions in AI and the digital economy could lead to better environmental sustainability. However, it is important to be careful with financial development to avoid bad outcomes. Policymakers should also consider the bidirectional relationship between AI innovation and the load capacity factor, suggesting that as AI advances, it can further enhance environmental sustainability, which in turn can create a favorable environment for more AI-driven solutions. Overall, a comprehensive approach that integrates technological advancement, financial regulation, and environmental sustainability is essential for the BRICS countries to gain long-term green growth.

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