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RESEARCH ARTICLE

Leveraging AI for Promoting Sustainable Environments in G-7: The Impact of Financial Development and Digital Economy via MMQR Approach

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Abstract
This study investigates the role of Artificial Intelligence (AI) in promoting a sustainable environment within the G-7 countries by testing the Load Capacity Curve (LCC) hypothesis. Additionally, it examines the effects of financial development, the digital economy, and urbanization on the load capacity factor using data from 2010 to 2022. The research employs cross-sectional dependence and slope homogeneity tests, revealing issues of cross-sectional dependence and heterogeneity. Panel unit root tests, both first and second generation, confirm that the variables are free from unit root problems. Furthermore, panel cointegration tests indicate that the variables are cointegrated in the long run. To assess the impact of the explanatory variables on the load capacity factor, the study utilizes the Method of Moments Quantile Regression (MMQR). The findings reveal a U-shaped relationship between income and the load capacity factor, supporting the LCC hypothesis in the G-7 region. The results also indicate that AI innovation and financial development have a significant positive correlation with the load capacity factor. In contrast, the digital economy and urbanization are found to significantly reduce the load capacity factor. Robustness checks, including the Driscoll-Kraay standard error, Augmented Mean Group, and Common Correlated Effect Mean Group estimation approaches, validate the findings obtained from the MMQR method. Moreover, the Dumitrescu-Hurlin (D-H) causality assessment is utilized to explore the causal connections between variables. The results reveal a unidirectional causal relationship between income and the load capacity factor. Additionally, bidirectional causal relationships are the remaining explanatory variables and load capacity factors.

Keywords: Artificial Intelligence; Digital Economy; Financial development; LCC Hypothesis; MMQR approach

Introduction

The urgency for improving the standard of ecological sustainability across national, regional, and global economies has attracted attention in recent years from policymakers and researchers (Ibrahim & Ajide, 2021, Raihan et al.2024a). It has been recognized that one vital cause of climate change is greenhouse gas emissions (Atasoy, 2017;

Destek and Sarkodie 2019, Islam et al.2023). About 75% of global emission statistics are attributed to carbon dioxide (CO_2) emissions, making it among the primary contributors to GHG emissions (Diffenbaugh, 2020, Pattak et al.2023). A reduction in emissions of less than 25% and 55%, respectively, must be achieved to meet the goal of reducing climate change to less than 2 °C and 1.5 °C by 2030 (UNEP, 2019, Raihan et al.2022a). To prevent devastating global climatic catastrophes, COP26 suggested that all nations aggressively embrace equitable growth methods and keep global temperature change to 1.5 °C (Murshed, 2021, Raihan et al.2023a). The seven nations considered vital for preserving a high standard of living in the world's economy are Japan, the US, Canada, Italy, Germany, France, and the UK (Saeed et al., 2024, Voumik and Ridwan, 2023). Several factors led to the selection of G-7. For example, The G-7 territory produces more than 60% of the globe's net financial assets as a consequence of their considerable economic endeavors (Alola et al., 2022). Then, the group's total usage of energy accounts for over 42% of global energy use (World Bank 2017). Then, through its annual conference, the group of seven has devoted itself for the past 20 years to developing green technology and reducing the generation of waste (Kirton, 2012, Raihan et al.2023b). Fourth, environmental damage remains an imminent threat to the G-7 countries, even with their advancement toward a sustainable economy (Khan et al., 2020). For example, the group produced around 38% of the total global emissions between 1960 and 2014 (World Bank 2017). Canada holds the greatest per capita energy use and GHG pollution among the G7. The country's performance regarding environmental policy is assessed as average because it continues to offer incentives for the use and extraction of fossil fuels. In terms of power consumption and release of greenhouse gases, the UK, Italy, and Germany do exceptionally well, while the USA and Japan perform quite poorly (Hao et al., 2020, Raihan et al.2022b). The non-homogeneous features of the nation make the representation seem fascinating. The findings of this research could assist the leading nations develop appropriate environmental strategies.

The G-7 nations, which have created complex nations, are growing remarkably in response to technological advances and changes in society (Balsalobre-Lorente et al.,2024). These economically advanced countries possess more complicated economies than other countries (Khan et al., 2022, Ridwan, 2023). The load capacity factor (LCF) is a substitute for the ecological condition in this work, which relies on conclusions from previous examinations by Wang et al. (2024), Voumik et al. (2024), Awosusi et al. (2022), and Shang et al. (2022). A detailed look at the needs imposed on air, land, and water by human beings, as well as the ability of earth's resources to meet and adapt to such demands, is made feasible by the LCF. One technique for assessing how sustainable human activity is concerning the earth's carrying capacity is the ecological footprint (EFP) accounting (Wackernagel & Rees, 1998; Hoekstra, 2009). Ecological footprint (EFP) and biocapacity are both of its components (Mir et al., 2022). Environmental deterioration puts the well-being of almost 80% of the world's population at risk (Wu et al., 2024). The past ten years have witnessed notable GDP expansion and achievement, especially in developing nations. This has placed a growing strain on ecological systems, resulting in biodiversity loss and a spike in greenhouse gas emissions (Esmaeili et al., 2023; Ayad et al., 2023; Yameogo et al., 2021). Numerous opportunities through which the financial sector might impact environmental quality have been discovered by previous research. For instance, liberalization of finance increases the volume of money that consumers and companies must allocate and consume, which results in a spike in pollution (Bekhet et al., 2016; Awosusi et al., 2021); and financial accessibility promotes excessive energy usage and investments in green technologies, which enhances green environment (Tamazian & Rao, 2010, Ridzuan et al.2023). With the development of IoT, AI, virtual reality (VR), blockchain, autonomous vehicles, and modern technologies, the digital economy is expected to become indispensable (Javaid et al.,2022; Tolstykh et al., 2019). Strong online payment verification is one example of how digital technologies have simplified transactions (Castelo-Branco et al., 2019). Out of the three categories, ecological sustainability has the highest opportunity to reap benefits from AI, with 93% of the SDG targets being positively impacted (Vinuesa et al., 2020, Urbee et al.2024). AI might

positively affect 79% of the SDGs. The Intergovernmental Panel on Climate Change (IPCC) highlighted that global pollution must drop to net zero by at least 2050 to preserve a "high confidence" level of limiting warming to manageable degrees (Masson-Delmotte et al., 2018). By 2030, AI-powered technologies are projected to help reduce worldwide emissions by 4% (Gawel & Herweijer, 2021, Voumik et al.2023a). According to certain research, urban environmental sustainability advances the digital economy (Ulucak & Khan 2020; Shobande & Ogbeifun 2021; Mondejar et al. 2021). However, ecological sustainability might decline as a result of the digital economy (Cheng et al. 2019; Avom et al. 2020). By connecting all aspects of business across the Internet, Moriset and Malecki (2009) contend that the DGE lessens reliance on physical locations.
With this background in mind, our investigation aims to figure out how the G-7 countries (Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States) are affected by financial development (FD), artificial intelligence (AI) innovation, GDP growth, and the digital economy (DGE) sing MMQR Approach from 1990 to 2018. Moreover, the DKSE, AMG, and CCEMG methodologies were employed to verify the reliability of the results. The motive is to deliver advanced ideas of the multifaceted relationships between these components while supporting the emergence of ecologically friendly methods and stable economic development in this region. In financial development, this investigation fills the need for more information about the LCF in the G-7 nations in light of AI innovation and the digital economy. Previous research highlighted the impacts of digitalization, emerging technologies, and globalization in finance on LCF. Other nations or areas have conducted multiple studies on LCF and associated variables. This research adds uniqueness to the G-7 economies instance. As far as we are aware, the experiment we undertook is the initial effort to conduct a thorough analysis of the literature on the LCF, and its significance comes from the fact that AI and DGE have not received much attention in previous research projects. Policymakers and strategy developers may be able to foster environmentally conscious behavior more effectively if they are aware of these elements.
The other part of this study falls into five sections. Section 2 covers the body of current literature. In part 3, we go over the data, method, and modeling. Section 4 provides research outcomes and discussions. Finally, section 5 reports its conclusion and suggestions for policymaking.

Literature Review

In various regions of the world, the complex interrelationships among ecological footprint, clean energy use, urbanization, and financial globalization have been the subject of several ongoing researches. We want to emphasize the innovative sides of our research, which we believe add value to this area of inquiry that is consistently expanding. As a result, the findings of previous studies that have shed light on the factors influencing economic growth, financial development, artificial intelligence (AI), urbanization, the digital economy, and environmental sustainability in the Group-7 countries have been compiled into six sub-sections within this component.
Since early economies prioritized increased production as a basis for the betterment of people, economic growth and a sustainable ecosystem are strongly connected (Kihombo et al.,2022, Voumik et al.2023b). Global researchers have been paying careful consideration to the link that exists between economic development, structural change, and environmental pollution in recent years (Dong et al., 2020). Environmental deterioration was revealed to be a result of higher GDP by Xue et al. (2022) utilizing the ARDL approach. In a similar vein, Bekhet al. (2017) observed that in Saudi Arabia, Oman, Qatar, and Bahrain, GDP development is linked to greater CO2 emissions. Additionally, the findings that a 1% increase in the Italian GDP over a longer period might turn into an 8.08% increase in CO2 pollution (Pattak et al.,2023). Multiple investigations also agreed with this outcome, such as Ali et al.(2020) in Malaysia, Voumik et al.(2023c) in Kenya, Ahmed et al.(2015) in Pakistan, Ahmed et al.(2020) in China and Saud et al.(2018) in BRI countries. Nevertheless, based on research conducted in the G-7, Balcilar et

al. (2018) assert that environmental quality in Germany and the UK is unaffected by growth in the economy. However, Ridwan et al. (2024) claim that both in the short and long run, GDP significantly lowers CO2 emissions in six South Asian economies. Raihan et al. (2024b) found that economic expansion somewhat reduced carbon dioxide emissions in their examination of the link between GDP growth and CO2 emissions in India. Similarly, Bento and Moutinho (2016) examined data for Italy from 1960 to 2011 using the ARDL technique and determined that GDP development lowers pollution levels in Italy. Moreover, Mehmood et al. (2023) examined the GDP stimulus of the Group of Seven area's efforts to reduce greenhouse gases from 1990 to 2020. This CS-ARDL study shows an inverse association between GDP and CO2 emissions.

The term artificial intelligence refers to automated cognition that was developed in the 1950s and has discovered effective applications in research as well as business (Hoang et al., 2022). Artificial intelligence (AI) can encourage sustainability across multiple sectors by reducing waste products, increasing asset availability, and delivering green solutions (Rakha, 2023). Blockchain technology and artificial intelligence (AI), in particular, can significantly sever the link between economic expansion and its detrimental effects on the natural world (Jiang et al., 2021; Meng and Zhao, 2022; Tsolakis et al., 1523). There are several advantages of using AI-powered sensors and equipment for real-time hazardous substance monitoring in-ground and plant matter (Singh & Kaur, 2022). Initially, in contrast to conventional experimental techniques, it enables the more accurate and consistent recognition of these chemicals. Second, it provides information in real time, allowing fast reactions to any potential contamination problems. Finally, it decreases the requirement for manual collection of information and analysis, which lessens manpower and improves the monitoring of the accuracy of processes (Jeong and Choi, 2022). Al-Sharafi et al. (2023) gathered information from Malaysia and Turkey to explore the factors influencing the adoption of AI products and their effect on environmental conditions. They found that while AI solutions can reduce expenses, conserve water and energy, and enhance the disposal of waste, their influence on environmental sustainability is rather small, especially in emerging territories. Stakeholders can offer the framework for making sensible choices, putting effective methods into practice, and developing strategies that encourage ecological sustainability through using AI and AIoT technologies (Bibri et al., 2024). Moreover, governments can promote openness, authenticity, and accountability in the manufacturing process by utilizing technology and AI. This will help to promote sustainable practices and lessen adverse environmental impacts (Hong and Xiao, 2024).

Environmental sustainability and financial development are connected in a complicated way, and financial progress can lead to environmental damage in certain instances. Nonetheless, robust regulatory bodies and their consistent green initiatives might lead to enhanced environmental standards and a healthier economic system (Birdsall and Wheeler 1993). Most research shows an adverse link between a sustainable environment and financial growth. However, numerous studies also found a positive link based on associated variables, including the nature of the industry, country classification, and financial system in the economy (Lyu et al., 2021; Usman et al., 2021; Zafar et al., 2019). According to Shahbaz (2013), in Pakistan, environmental degradation might worsen as a result of financial uncertainty. By organizing countries into three income categories, Nasreen and Anwar (2015) discovered that, within the low-income panel, financial development (FD) increased damage to the environment, while in the high-income panel, it declined. According to Sharma et al. (2020), rising Asian nations' environmental impacts are positively influenced by financial growth. In addition, by raising the EF, financial development causes environmental damage in emerging regions (Ahmad et al., 2022). As per certain analyses (Zhang, 2011; Shahbaz et al., 2016), expansion in finances protects the level of the ecosystem by reducing emissions of greenhouse gases. Using OLS, PQR, and CCEMG methodologies, Ali et al. (2023) reviewed the effects of financial development on the ecological health of the E-7 bloc. They concluded that the region's environmental deterioration is exacerbated by financial development. Financial growth, based on Lv and Li (2021), can enhance the level of biodiversity, specifically in areas where it becomes more expanded and developed.

Furthermore, Shoaib et al. (2020) observed that financial expansion had an uplifting impact on CO2 emissions in G8 and D8 territories employing the pooled mean group technique. However, Dogan and Turkekul (2016) illustrated that monetary improvement is not a factor in the US's ecological degradation.

The term "digital economy" refers to economic activity, including online transactions across various platforms and technologies, including mobile, large-scale data, the Internet, and information and communications technology (Javaid et al.,2024). Many investigations on the financial and social implications of DGE have been conducted by academics. From a small-scale perspective, DGE might reduce both the degree of information asymmetry and alleviate businesses' financial limitations by utilizing modern digital technologies. Liu (2023) suggests that the expansion of the DGE may have a moderating implication on discharges of pollution. Raihan et al. (2024c) conducted research in the G-7 region from 1990 to 2019 to check the consequences of DGE on carbon emission. Utilizing the ARDL model showed that the digital economy significantly promotes a green ecosystem. Jiang et al. (2024) illustrate that the digital economy ensures environmental sustainability and can cut emissions by up to 0.092 %. Yuan et al. (204) adopted the spatial econometric model based on panel data from 267 Chinese cities from 2012 to 2021. They found that DGE could significantly lower harmful emissions. Similarly, several studies in different areas also found that (Ma et al.,2024; Dong et al.,2022; Bai et al.,2022; Che and Wang, 2022; Li et al.,2022). The influence of a shared digital economy on environmental pollution is yet unknown (Jin et al.,2018). According to Kuntsman and Rattle (2019), the improvement, maintenance, and disposal of modern innovative technologies have all had a substantial detrimental impact on natural health. According to Zha et al. (2022), the growth of the digital economy can successfully enhance the environmental sustainability of neighboring cities while simultaneously mitigating the CO2 pollution intensity of a particular region. In developing nations, DGE increased carbon emissions, based on Danish et al.(2019), who used information from 73 countries and the modified ordinary least squares (OLS) approach.

The phenomena of urbanization have a noteworthy implication on the condition of the natural world. The greater need for energy, resources from nature, and additional services generated by urbanization will eventually have a detrimental impact on the ecosystem. Numerous authors, such as Arshad et al. (2020) for Asian economies, Nathaniel et al. (2021) for Latin American and Caribbean countries, Van et al. (2018) for Australia, and Mahmood et al. (2020) for Saudi Arabia, have explored the link among urbanization, GHG emissions, and the environmental impact. Arslan et al.(2022) indicated that urban population expansion accelerates ecological deterioration. For ASEAN nations, Nathaniel and Abdul (2020) investigated the link between urbanization and ecological footprint (EFP) between 1990 and 2016. According to their research, urbanization increases the EFP, which reduces environmental sustainability. Utilizing unique panel data approaches from 2000 to 2020, Feng and Li (2024) demonstrated that urbanization continues to be a leading element in rising ecological degradation in the ASEAN-6 economies. Surprisingly, Xue et al. (2022), utilizing the ARDL approach, discovered that urbanization reduced pollution in the third-largest European country, France, from 1987 to 2019. Ahmad et al. (2021) demonstrated that urbanization improves ecological sustainability by lowering the ecological footprint, especially measured by FMOLS and DOLS. Mehmood (2021) discovered that urbanization in the SAARC area increased air quality between 1996 and 2015. Moreover, Azam and Khan (2016) investigated how urbanization affected environmental degradation in Bangladesh, India, Sri Lanka, and Pakistan between 1982 and 2013. The outcomes showed that, while there was a negative correlation in Bangladesh and India, there was an encouraging correlation in Sri Lanka and Pakistan between urbanization and environmental degradation.

The methods of knowledge accumulation related to the digital economy (DGE), artificial intelligence (AI) innovation, and the real effect of financial growth on load capacity factor (LCF) remain unclear, regardless of the G-7 nations' promising sustainable environment quality. From the standpoint of the G-7, aspects like artificial intelligence (AI), the digital economy, and financial development are entirely novel fields of investigation.

Furthermore, the MMQR Approach, which has not been widely implemented in prior LLC studies, is used in our work. This approach enables the effective assessment of data from panel models, consequently augmenting the discipline's methodological understanding. Through an analysis of all of these standards, the nations selected can assess whether harnessing innovations in technology, economic collaboration, and sustainable growth may offer the possibility to improve their sustainability issues. Therefore, by examining the dynamic impacts of GDP, DGE, FD, and AI on LCF and employing different advanced econometric methodologies, this present study intends to close the deficiency in the literature for the instance of Group Seven nations.

Methodology

Data and Variables

The research gathers yearly data for the G-7 from four sources for the years 1977–2018. Our World in Data indicates that the digital economy indicates ICT goods imports (% of total goods imports), and artificial intelligence reflects patent applications in the field of AI. The World Bank provided the statistics used to calculate GDP and GDP2, which are expressed as (Current US$). The load capacity factor (LCF) (biocapacity/ecological footprint) is derived from data from the Global Footprint Network. Lastly, the IMF's Financial Development Index is a collection of financial development data.

Table 1: Data and Variables

Variables	Description	Logarithmic Form	Unit of Measurement	Source
LCF	Load Capacity Factor	LLCF	Gha per person	GFN
GDP	Gross Domestic Product	LGDP	Current US$	WDI
GDP^2	Gross Domestic Product Square	$LGDP^2$	Current US$	WDI
AI	Artificial Intelligence Innovation	LAI	Patent Application in AI Field	Our World in Data
FD	Financial Development	LFD	Financial Development Index	IMF
DGE	Digital Economy	LDGE	ICT goods imports (% of total goods imports)	Our World in Data
URBA	Urbanization	LURBA	Urban Population (% of total population)	WDI

Theoretical Framework

The LCC theory is based on the LCF indicator, which takes alternatives for environmental provision and manmade needs for the environment into account. The LCF initially appeared in the literature by Siche et al. (2010), and Pata (2021) was the very first to do empirical studies on the variables that influence the LCF. By differentiating the ecological footprint and biocapacity, the LCF enables thorough environmental quality assessment (Dogan and Pata,2022). The LCF enables both the supply and demand sides to examine the ecosystem, and a more favorable environment is shown by a higher LCF (Pata and Kartal, 2023). Scholars have developed advanced techniques to measure the implications of manmade activities on ecology and evaluate how long the planet will survive these effects. With the use of these methods, the LCC evolves into an invaluable instrument for integrating intricate data into an accessible framework by considering the association between human actions and the clean environment. The components of GDP growth, financial development, artificial intelligence (AI), urbanization, digital economy, and load capacity factor may be related in several ways, as already mentioned. For the LCC hypothesis, we have developed the following equation (1) to expand our understanding of prior studies:

$$\mathrm{Load\ Capacity\ Factor} = \mathrm{f}(\mathrm{GDP}, \mathrm{GDP}^2, \mathrm{K_t}) \qquad (1)$$

Here, $\mathrm{K_t}$ is a factor for additional parameters impacting the LCF, while GDP is a variable for income in equation (1). Equation (2) tries to illustrate a broader understanding of the elements impacting the LCF.

$$\mathrm{LCF} = \mathrm{f}(\mathrm{GDP}, \mathrm{GDP}^2, \mathrm{AI}, \mathrm{FD}, \mathrm{DGE}, \mathrm{URBA}) \qquad (2)$$

While the labels financial development (FD), artificial intelligence (AI), urbanization (URBA), and digital economy (DGE) serve to depict particular concepts, the load capacity factor in equation (2) is portrayed by LCF. An econometric explanation of this equation is provided below.

$$\mathrm{LCF_{it}} = \rho_0 + \rho_1 \mathrm{GDP_{it}} + \rho_2 \mathrm{GDP_{it}^2} + \rho_3 \mathrm{AI_{it}} + \rho_4 \mathrm{FD_{it}} + \rho_5 \mathrm{DGE_{it}} + \rho_6 \mathrm{URBA_{it}} \quad (3)$$

The logarithmic outcomes of the elements are displayed in equation (4), which improves interpretation and simplifies the formulation of statistical findings. These transformations can deal with heteroscedasticity and accept information with various magnitudes, making them effective in reducing the implications of data with an extensive range. Moreover, the research's coefficients are represents in the parameter range of ρ_0 to ρ_6 in equation (4).

$$\mathrm{LCF_{it}} = \rho_0 + \rho_1 \mathrm{LGDP_{it}} + \rho_2 \mathrm{LGDP_{it}^2} + \rho_3 \mathrm{LAI_{it}} + \rho_4 \mathrm{LFD_{it}} + \rho_5 \mathrm{LDGE_{it}} + \rho_6 \mathrm{LURBA_{it}} \quad (4)$$

Econometric Framework

The link between LCF and some independent factors in the G-7 nations was investigated in this study using the MMQR approach for data estimation. We additionally employed the DKSE, AMG, and CCEMG approaches to guarantee robustness. To begin with, we checked for dependence and stationarity using the CSD and Panel unit root analyses. We subsequently carried out the cointegration and MMQR estimation. Finally, the D-H causality method was utilized to determine the causal links among the selected factors.

Cross-Sectional Dependence test

Cross-sectional dependence (CSD) can arise from unidentified reasons that distort the correct values, thereby decreasing the usefulness of panel data. When the CSD problem is avoided in panel data, can end up in misleading outcomes (Waris et al., 2023). As countries grow increasingly integrated and dependent on one another, industrialization is making CSD a greater problem in panel data (De Hoyos and Sarafidis, 2006). Our study will initially utilize the CSD testing created by Pesaran (2015) in each cross-sectional unit to predict the existence of CSD before starting the empirical portion of the investigation. So, in order to illustrate the test's statistics, the below equation can be taken:

$$CSD = \sqrt{\frac{2T}{N(N-1)N}\left(\sum_{i=1}^{N-1}\sum_{K=i+1}^{N}\widehat{Corr_{i,t}}\right)} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

Panel Unit root test

We used the LLC test, developed by Levin et al. (2002), and the second-generation panel unit roots assessment, introduced by Pesaran (2007), taking into account any potential cross-sectional independence within the panel time-series information. These tests include the cross-sectional augmented Dickey-Fuller (CADF) panel unit root tests and the cross-sectional IPS (CIPS), which is an extension of the IPS panel unit root test that was established by Im et al. (2003). Based on the alternative hypothesis that at least one individual series in the panel is stationary and the null hypothesis that all individual series within the panel are stationary, the CIPS and CADF panel unit root methods are conducted (Ssali et al.,2019). The LLC test statistics can be displayed in the following way:

$$\Delta y_{it} = \beta_i y_{it-1} + \sum_{j=1}^{\vartheta i} d_{ij}\Delta y_{it-1} + M'_{it}\varphi + \mu_{it} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(6)$$

Here, M'_{it} represents the column vector of the independent variable and in regression φ denotes the vector of parameters.

By incorporating heterogeneity in the coefficient of $y_{i,t-1}$, Im et al. (2003) expanded the LLC test and introduced a test strategy named the IPS unit root test that utilized the mean of each participant's unit root statistics. The equation underlying the IPS unit root test is as follows:

$$\Delta Y_{i,t} = \beta_i + \gamma_{i,t} + \delta y_{i,t-1} + \sum_{j=1}^{k}\theta_k \Delta y_{i,t-j} + \mu_{i,t} \qquad (7)$$

In contrast to traditional unit root tests, Pesaran's (2007) novel approach, CIPS, enables heterogeneity resilient to CSD and provides more consistent and trustworthy findings (Harris and Tzavalis 1999; Im et al. 2003; Levin et al. 2002). The CIPS test is examined using equation (8):

$$CIPS = \frac{1}{N}\sum_{t=1}^{N} t_1(N,T) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (8)$$

Where N means a cross-sectional aspect, and T means time series dimension. Moreover, equation (8) provides the following method for computing the CADF:

$$\Delta Yi_t = \delta_i + \rho i Yi_{t-1} + \delta i \bar{Y}_{t-1} + \sum_{j=1}^{\vartheta}\omega_{ij}\bar{Y}_{t-1} + \sum_{j=1}^{p}\alpha_{ij}\,\Delta Y_{i,t-1} + \varepsilon_{it} \ldots\ldots\ldots (9)$$

Where $\bar{Y}_{t-1}$ and $\Delta Y_{i,t-1}$ symbolize the average values of the cross-sectional analysis for both the first difference and lag.

Panel Cointegration test

The Pedroni panel cointegration examination is utilized to check if cointegration prevails, assuming panel heterogeneity (Raihan et al.,2024). Pedroni's (1999) panel cointegration test is utilized in this work, which has two separate assessments. Panel v-statistics, panel rho-statistics, panel PP-statistics, and panel ADF-statistics are the four statistical measures used in the first test, which uses a within-dimension method. Group rho-statistics, group PP-statistics, and group ADF-statistics are the three statistical measures used in the second test, which employs a between-dimension technique. Both the homogeneous (panel) and interdimensional (group) versions of Pedroni's statistics are of the ADF and PP categories (Lugo-Arias et al., 2024). The null hypothesis that there exists no cointegration is rejected if the majority of these data have p-values that are less than a predetermined significance threshold. The general regression residuals for the proposed co-integration regression are provided below:

$$y_{i,t} = \omega_i + \delta_i t + \rho_{1i}x_{1i,t} + \rho_{2i}x_{2i,t} + \cdots + \rho_{Mi}x_{Mi,t} + \varepsilon_{i,t} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (10)$$

for, t = 1,…..T; i = 1,…, N; m = 1,…, M

The null hypothesis of the no-cointegration test is denoted as $H_0 : f_i = 0; \forall_i$ (absence of cointegration).

Method of Moments Quantile Regression

This study uses Machado and Silva's (2019) invention, the moments' regression approach (MM-QR), to determine the quantiles. In contrast to conventional quantile regressions, the MMQR evaluates the objectives by modifying the mean values, allowing "conditional heterogeneous covariance implications" by Koenker (2004) and Canay (2011) to affect and accomplish the dependent variable's obtaining over the whole data distribution. Furthermore, this technique allows for location-dependent imbalance as the variables are sensitive to their position within the distribution circumstances (Hieu and Mai,2023). All these suggest that the MMQR is more acceptable and robust, especially when it comes to addressing the issues of heterogeneity and endogeneity (An et al., 2021) and developing asymmetrical nonlinear associations (Elbatanony et al., 2021). The alternative model is listed as follows:

$$Y_{it} = \beta_i + X_{it}\gamma + (\vartheta_i + Z_{it}\varphi)U_{it} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(11)$$

Where the probability is $P\,\{\vartheta_i + Z_{it}\varphi > 0\} = 1$. Additionally, parameters such as $\beta, \gamma, \vartheta,$ and φ are required to be calculated. Moreover, in $\beta_i, \vartheta_i i = 1$…….., n denotes 'individual fixed effect, and Z represents the k vector of component X". Furthermore, the elements are transformed with component m given below:

$$Zm = Zm\,(X), m = 1, \ldots \ldots \ldots, k \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(12)$$

Here, U_{it} is orthogonal to X_{it} and consistent in fulfilling the moment conditions, which do not include stringent heterogeneity. Hence, the conditional quantile of Y is mentioned below:

$$Q_\tau\left(\frac{\tau}{X_{it}}\right) = \left(\beta_i + \vartheta_i q\,(\tau)\right) + X_{it}\gamma + Z_{it}\varphi q(\tau) \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots(13)$$

In this equation, X_{it} symbolizes the predictive variables such as GDP, GDP^2, AI, FD, DGE, and URBA. On the other hand, Y_{it} represents the dependent variable like LCF. It's important to keep in mind that changing the intercept does not take into account a person's influence when OLS is utilized, and a consequence comes from fixed effects. Now, $Q(\tau)$ can be estimated as follows:

$$Min_q = \sum_t \sum_i p\tau(R_{it} - (\vartheta_i + Z_{it}\varphi q)) \ldots\ldots\ldots\ldots\ldots.(14)$$

Robustness Check

This phase involves performing three separate tests: the DKSE introduced by Driscoll and Kraay (1998), the AMG estimator created by Bond and Eberhardt (2009) and Eberhardt and Teal (2011), and the CCEMG estimator introduced by Pesaran (2006). In contrast to traditional standard errors, DKSE takes into consideration slope heterogeneity, average CSD, and correlated errors that might occur between observations. This helps to reduce the possibility of biases and inefficiencies during parameter estimation (Ridwan et al., 2024). Because of the slope of heterogeneity and the CSD problem, we thus utilized the AMG estimator in line with Nathaniel et al. (2020); and Murshed et al. (2021). Furthermore, because AMG considers the endogeneity issues and calculates the elasticity of particular nations, it offers several advantages over conventional panel methodologies (Isik et al., 2021). In addition, findings are better suited when the time exceeds the cross-sectional unit (Shahzad and Aruga, 2023). The identification challenge is resolved by the CCEMG by taking into consideration temporal variations with various pitch variables (Raihan et al.,2024). The AMG is a specific way of treating CCEMG that takes into account yearly inefficiency and neglected aspects in addition to cross-dependence, heterogeneity, and structural and technology developments (Polcyn et al., 2023).

D-H Causality Test

Causality tests are necessary to determine the consequences of particular policies that address environmental pollution. Granger (1969) established an assessment for assessing the elements' causal connections. In our present work, we utilize the D-H panel causality examination, an advanced measure of causality that was created by Dumitrescu and Hurlin (2012). This method is extremely comprehensive and beneficial in producing reliable outcomes throughout CSD as it allows for both N > T and T > N samples (Ahmed and Le, 2021). According to Dumitrescu and Hurlin (2012), the alternative hypothesis asserts that there is at least one Granger causality relationship between cross-sections, while the null hypothesis claims that there is no Granger causality link between cross-sections. The causality of the D-H panel may be written as:

$$y_{it} = \theta_i + \sum_{j-1}^{j} \delta_i^j y_{i(t-j)} + \sum_{j-1}^{j} \gamma_i^j x_{i(t-j)} + \varepsilon_{it} \qquad (15)$$

Here, x and y represent the observables, δ_i^j represents the autoregressive parameter, and γ_i^j denotes the estimations of the regression coefficients

Results and Discussion

Summary Statistics

Based on 91 observations, the summary statistics for the factors we explored can be seen in Table 02 below. A total of seven factors are presented in the G-7 nations' descriptive statistics: LLCF, LGDP, LGDPSQ, LAI, LFD, LDGE, and LURBA. All of the chosen variables—aside from LLCF and LFD—have positive means, as the table illustrates. Furthermore, each variable's estimated standard deviation is small, suggesting that the data points are mostly concentrated around the mean with minimal fluctuation. While LFD and LURBA suggest negative skewness, a lot of variables show positive skewness. The Jarque-Bera normality assessment was applied to establish that all the variables had a normal distribution that took skewness and kurtosis into consideration.

Cross-Sectional Dependence test

To confirm if the CSD is present in our data set or not, Table 03 displays the results of the CSD assessment. The CSD statistics for all variables are regarded as statistically significant at conventional levels because of the extremely low p-values. All variables have p-values of 0.000, except LFD, where the p-value is 0.043. Taken together, these data provide strong evidence of cross-sectional correlation at the 1% level. It indicates that our data collection contains a CSD problem. Thus, we may infer that there is a cross-sectional dependence problem with lnLCF, lnGDP, lnGDP2, lnAI, lnFD, lnDGE, and lnURBA.

Table 2: Summary statistics of the variables

Statistic	LLCF	LGDP	$LGDP^2$	LAI	LFD	LDGE	LURBA
Mean	-0.190398	10.69067	114.3221	5.522956	-0.190398	2.120523	4.387441
Median	-1.121269	10.67368	113.9275	5.513429	-0.178789	2.056207	4.397432
Maximum	0.723357	11.24282	126.4009	9.709417	-0.06901	2.670226	4.521299
Minimum	-2.038284	10.317	106.4405	1.609438	-0.400781	1.569931	4.224305
Std. Dev.	0.779588	0.178842	3.840701	2.003691	0.08979	0.316546	0.075888
Skewness	0.811059	0.519595	0.575074	0.220978	-0.496358	0.255469	-260761
Kurtosis	2.868482	3.496751	3.583357	2.426018	2.141739	2.09277	3.070021
Jarque-Bera	10.04246	5.030319	6.306099	1.989793	6.529623	4.110635	1.049867
Probability	0.006596	0.08085	0.042722	0.369762	0.038204	0.128052	0.591595
Sum	-85.88593	972.851	10403.31	502.589	-17.32621	192.9676	399.2571
Sum Sq. Dev.	54.69818	2.878612	1327.589	361.3301	0.72561	9.018143	0.51831
Observations	91	91	91	91	91	91	91

Table 3: Results of Cross-Sectional Dependence test

Variables	CD Statistics	P-Value
LLCF	4.84***	0.000
LGDP	5.36***	0.000
$LGDP^2$	5.37***	0.000
LAI	13.33***	0.000
LFD	3.06**	0.043
LDGE	8.73***	0.000
LURBA	16.21***	0.000

Panel Unit root test

Table 4 presents the findings from the unit root testing. The LLC and IPS assessments were the first-generation unit root methods, and the CIPS and CADF analyses were the second-generation unit root tests employed in this investigation. LAI, LFD, and LDGE are the only ones that show stationary behavior at the level form I(0), based on the LLC test findings. At the 1% significance threshold, all of the remaining elements are significant and stationary at the first difference form I(1). The results of the IPS test suggest all other variables are stationary at the first difference form, except LFD and LDGE. On the other hand, LFD and LDGE are significant at the 1% and 5% levels of significance, respectively, and stationary at the level form. The other factors (LLCF, LGDP, LGDP2, LFD, and LURBA) are stationary at the first difference form I(1) and significant at the 1% level of significance, according to the CIPS test, while LAI and LDGE are stationary at the initial level and significant at the 5% level of significance.

Comparably, the CADF unit root test reveals that all variables, except for LAI and LFD, which are stationary at the level form I(0) and significant at the 5%, are stationary at the first difference form I(1). Therefore, before we considered their initial differences, LCF, GDP, GDP2, and URBA were not stationary; as a result, they became stationary in all four unit root evaluations. Conversely, in the level form I(0), LAI, LFD, and LDGE are stationary. We can move on with the assessment utilizing the MMQR framework because of this mixed order of integration.

Table 4. Panel Unit Root test

Variables	Levin, Lin &Chu		IPS		CIPS		CADF		Decision
	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	
LLCF	-2.392	-5.032***	-0.801	-3.457***	-0.629	-3.968***	-1.032	-3.781***	I(1)
LGDP	-0.742	-5.749***	-1.216	-4.407***	-1.532	-3.409***	-1.231	-3.801***	I(1)
$LGDP^2$	-0.767	-5.759***	-1.415	-4.016***	-1.288	-3.894**	-1.517	-3.776***	I(1)
LAI	-5.800***	-5.103***	-1.251	-4.001***	-2.243**	-4.098***	-3.023**	-3.838***	I(0)
LFD	-5.061***	-6.091***	-3.245**	-4.600***	-1.078	-3.558***	-2.981**	-3.812***	I(0)
LDGE	-5.009***	-6.881***	-3.980***	-4.436***	-3.098**	-5.462***	-1.530	-3.480***	I(0)
LURBA	-0.132	-4.267***	-2.599	-7.924***	-0.659	-3.859***	-0.882	-3.087**	I(1)

Panel Cointegration test

The findings of the Panel cointegration examination are presented in Table 05. Two distinct sets of alternative hypotheses are evaluated in the test: one for common autoregressive coefficients within and one for individual autoregressive coefficients between dimensions.

The Panel rho-statistic is positive but not statistically significant; in addition, the Panel v-statistic is positive but not statistically significant, indicating mixed proof for cointegration. Nonetheless, the extremely significant Panel PP and Panel ADF-Statistic results provide strong evidence to reject the null hypothesis that there is no cointegration. The null hypothesis that there is no cointegration across panels is strongly rejected by the Group PP and Group ADF-Statistic, which are both considerably negative. Under the assumption of individual autoregressive coefficients between dimensions, the Group rho-statistic is positive but not significant. The analysis shows that there is still an indication of cointegration throughout the variables in the overall dataset, even in the context of considerable disparities in autoregressive coefficients within and across aspects.

Table 5: Panel cointegration test

Alternative hypothesis: common AR coefs. (within-dimension)				
	Statistic	Prob.	Weighted Statistics	Prob.
Panel v-Statistic	1.86726	0.0309	0.41145	0.3404
Panel rho-Statistic	1.70292	0.9557	2.97131	0.9985
Panel PP-Statistic	-4.44973	0.0000	-2.07019	0.0000
Panel ADF-Statistic	-5.01670	0.0000	-2.89741	0.0000
Alternative hypothesis: individual AR coefs. (between-dimension)				
	Statistic	Prob.		
Group rho-Statistic	4.20741	0.9761		
Group PP-Statistic	-5.76269	0.0000		
Group ADF-Statistic	-3.27079	0.0000		

Method of Moments Quantile Regression

The outcomes of the MM-QR technique are presented in Table 10. The estimated coefficient of LGDP has a strong and negatively significant implication on LLCF, indicating that a growth in per capita GDP greatly upsurges environment pollution at all quantile levels. The findings of the study align with the results of Adebayo et al. (2021) for South Korea, Orhan et al. (2021) on India, Ridwan et al. (2023) linked to France, Ahmad et al. (2024) regarding China, Pata and Samour (2023) in France, and Adebayo and Rjoub (2021) in terms of the MINT areas. Additionally, Destek et al. (2020) discovered that in the G-7, higher GDP is associated with increased emissions of CO2 and expressed that greater economic activity which usually entails burning fossil fuels for energy is a direct result of economic expansion. Furthermore, Chien et al. (2023) have shown that growth in the economy often increases people's financial resources, which raises consumption levels and degrades the environment in the G-7 region. However, some authors disagree with this consequence and reveal that development in GDP can upgrade the environmental quality (Voumik et al., 2022; Nica et al., 2020). The coefficient of LGDP2 is positively significant at all quantiles. Our findings of LGDP2 illustrate that financial expansion over time recovers environment pollution by adopting clean power and utilizing technology into manufacturing process. The finding aligns with the outcome of Bunnag (2023) for Thailand.

There is a substantial and encouraging relationship between artificial intelligence (LAI) and LLC in all quantiles. AI innovation creates better opportunity for individuals to use green technology and highlights the utilization of technologies for green ecosystem. By modernizing China's manufacturing facilities, AI can have an advantageous systemic impact on lowering the intensity of environmental pollution (Zhao et al.,2023). The use of AI technology in ecological damage prevention was also highlighted by Ye et al. (2020).

Moreover, in all quantiles, the digital economy is inversely and significantly related to LCF. This indicates that a digitalized economy is not good for ensuring a sustainable environment in the G-7 area. Wang et al. (2022) show that China's CO2 pollution might mitigate as long as the digital economy grows. Similarly, Usman et al. (2021) align with this conclusion in certain Asian countries. However, Raihan et al.(2024) opposed this conclusion and revealed that in G-7 countries, DGE improves environmental sustainability. Moreover, by influencing residential energy decision-making and individual ecologically conscious actions, digital technology can decrease energy use and encourage ecologically sound growth (Chiabai et al., 2013; Bastida et al., 2019).

Conversely, LFD beneficially affects LLCF, which indicates that it promotes a clean environment, and the outcomes are significant at 1% across all quantiles. This conclusion conflicts with those of (Xu et al., 2018) in Saudi Arabia, Ahmad et al. (2022) in 17 developing nations, Weili et al.(2022) in the Belt and Road countries, and Shehzad et al. (2022) in Pakistan. On the other hand, Durani et al. (2023) revealed that financial development causes ecological destruction in BRICS nations. Furthermore, Ibrahim et al. (2023) proposed that the BRICS countries' ecosystem condition declines due to financial growth.

Lastly, from the table, we can see that urbanization is negatively associated with the LCF variable across all quantiles. This outcome indicates the necessity of sustainable urban planning for the sustainable environment of the chosen area. Furthermore, URBA stresses ecosystems by causing forest loss, the loss of agricultural area, and the production of hazardous waste (Winoto and Schultink, 1996). The conclusions seem consistent with those of Anser et al. (2020), Azam and Khan (2016), and Gasimli et al. (2019). However, Kim (2020) discovered that Korea's rebound effect and high energy efficiency imply that URBA has no impact on pollution.

Table 6: Method of Moments Quantile Regression

VARIABLES	Location	Scale	(1) Q0.05	(2) Q0.25	(3) Q0.50	(3) Q0.75	(4) Q0.95
LGDP	-0.160***	-0.842**	-0.652***	-0.721***	-0.185***	-0.434***	-0.145**
	(0.5712)	(0.2711)	(0.0831)	(0.2351)	0.4924)	(0.6211)	(0.9215)
$LGDP^2$	0.409***	0.0343**	0.469***	0.441***	0.310***	0.379***	0.326**
	(0.098)	(0.618)	(0.355)	(0.113)	(0.094)	(0.333)	(0.047)
LAI	0.126**	-0.00539	0.135***	0.131**	0.126**	0.121**	0.113***
	(0.0517)	(0.0291)	(0.0638)	(0.0524)	(0.0515)	(0.0628)	(0.0964)
LDGE	-0.096***	-0.354**	-0.470***	-0.766***	-0.086***	-0.406***	-0.948***
	(0.309)	(0.174)	(0.377)	(0.317)	(0.316)	(0.373)	(0.586)
LFD	0.637***	0.638*	0.508***	0.042***	0.620***	0.195***	0.173***
	(0.676)	(0.381)	(0.827)	(0.691)	(0.685)	(0.818)	(0.274)
LURBA	-1.124*	1.041*	-0.965***	-0.094***	-0.151***	-0.213	-0.382
	(0.109)	(0.625)	(0.358)	(0.134)	(1.123)	(1.343)	(2.091)
Constant	-21.7***	1.797	-24.912***	-23.478***	-21.853***	-20.211***	-17.409**
	(12.212)	(9.950)	(15.380)	(13.034)	(13.809)	(12.901)	(9.621)
Observations	91	91	91	91	91	91	91

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

Robustness Check

The DKSE, AMG, and CCEMG evaluations, which were performed to confirm the reliability of our estimations, can be seen in Table 7. We examine the implications of GDP, GDP squared, urbanization, digital economy, artificial intelligence (AI), and financial development (FD) on LCF. The findings support the conclusions from the MM-QR regression, indicating that LCF significantly decreases as GDP per capita increases. Specifically, the estimators DKSE, AMG, and CCEMG show a decline in LCF of approximately 0.168%, 0.177%, and 0.210%, accordingly, for a 1% expansion of GDP. On the other hand, economic development over time leads to a spike in LCF by 0.209% (DKSE), 0.294% (AMG), and 0.139% (CCEMG), which is in line with the results of the MM-QR regression. Similarly, a 1% rise in AI causes a boost in LCF by 0.126% in DKSE, 0.042% in AMG, and 0.019% in CCEMG. This conclusion highlights the favorable consequence of AI technology on environmental sustainability in the G-7 region and is consistent with the MMQR analysis.
Additionally, the DKSE, AMG, and CCEMG estimators demonstrate an upward correlation between financial development and LCF, with a 1% increase in FD interpreting into a rise in LCF of 0.637%, 0.629%, and 0.650% in the Group-7 region. These results are consistent with the results of the MMQR method. On the other hand, the digital economy is unfavorably related to LCF in DKSE (−0.096), AMG (−0.065), and CCEMG (−0.289), with a 1% significance level for the first two estimations. These findings, in addition to those from the MM-QR regression, corroborated the idea that the adoption of the DGE degrades environmental quality. Differential effects of urbanization on LCF are observed in DKSE, AMG, and CCEMG. At the 5% level of significance, the urbanization coefficient in DKSE (-0.124) and AMG (-0.842) is detrimentally significant. Conversely, the CCEMG calculation displays that the coefficient is destructively significant (−0.844) at the 10% significance

threshold. The above findings confirm the adverse influences of urban population increase on ecosystem conditions in the G-7 countries and are following the MMQR technique.

Table 7. Robustness Test

VARIABLES	(1) DKSE	(2) AMG	(3) CCEMG
LGDP	-0.168***	-0.177***	-0.210*
	(0.0522)	0.0143)	(0.0255)
LGDP2	0.209***	0.294***	0.139**
	(0.5091)	(0.4940)	(0.5313)
LAI	0.126***	0.042***	0.019**
	(0.0585)	(0.0726)	(0.0662)
LFD	0.637***	0.629***	0.650**
	(0.316)	(0.800)	(0.620)
LDGE	-0.096***	-0.065***	-0.289
	(0.296)	(0.262)	(1.470)
LURBA	-0.124**	-0.842**	-0.844*
	(1.380)	(15.78)	(100.9)
Constant	-21.712***	-29.411**	32.317
	(16.800)	(15.611)	(17.188)
Observations	91	91	91
Number of groups	7	7	7
R-squared	0.9221	0.9023	0.9065

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

D-H causality test

The Dumitrescu & Hurlin causality assessment results are summarized in Table 8. We could reject the null hypothesis as the research shows unidirectional causation between LGDP and LLCF, and the corresponding p-value is below the traditional significance thresholds. Similarly, with a p-value of 0.0197, LGDP2 Granger causes LLCF, suggesting that faster economic development has a major effect on LCF in the G-7 region. Furthermore, the p-value for LAI is 0.0017, which is under the accepted 0.05 significance threshold. We might therefore infer that LAI Granger causes LLCF and reject the null hypothesis. Additionally, there prevails a bidirectional causal relationship (p-values of 0.0064 and 0.0195, respectively) between LFD and LCF, demonstrating that changes in one factor also affect the other. Furthermore, as the p-values for LDGE and LCF are below the traditional level, suggesting that both variables Granger cause one another, there is a bidirectional causal connection between them. Furthermore, with p-values of 0.0268 and 0.0066, LURBA Granger causes LLCF and vice versa. Because the p-values are below the conventional level, we could dismiss the null hypothesis. In contrast, there exists no significant causal connection as displayed through p-values greater than the normal significance threshold for the relationships between LLCF and LGDP, LLCF and LGDP2, and LLCF and LAI. Thus, in these instances, we cannot rule out the null hypothesis that there is no existence of causality.

Table 8. D-H Causality Test

Null Hypothesis	W-Stat.	Zbar-Stat.	Prob.
LGDP $\neq$ LLCF	2.52997	1.43133	0.0123
LLCF $\neq$ LGDP	0.91328	-0.42843	0.1383
LGDP2 $\neq$ LLCF	2.5697	1.47704	0.0197
LLCF $\neq$ LGDP2	0.91717	-0.42395	0.6716
LAI $\neq$ LLCF	0.66013	-0.71964	0.0017
LLCF $\neq$ LAI	2.84746	1.79655	0.0724
LFD $\neq$ LLCF	0.18725	-1.26362	0.0064
LLCF $\neq$LFD	2.15102	0.9954	0.0195
LDGE $\neq$ LLCF	0.39599	-1.0235	0.0061
LLCF $\neq$ LDGE	1.73064	0.51182	0.0088
LURBA $\neq$ LLCF	3.21109	2.21486	0.0268
LLCF $\neq$ LURBA	2.72999	1.66142	0.0066

Conclusion and Policy Implications

The load capacity factor (LCF) in the Group-7 countries was extensively examined in our research from 1990 to 2022 concerning artificial intelligence (AI), economic growth, financial innovation, the digital economy, and urbanization. The analysis uses sophisticated econometric techniques to validate the Load Capacity Curve (LCC) hypothesis, and the results provide important insights into the complicated connections between financial activities and the well-being of the natural world. The findings of the stationarity analyses demonstrate that there are no unit root difficulties and that the parameters exhibit varying degrees of integration. The LCC hypothesis is confirmed in both the short and long term in the Group-7 region by the MMQR calculations, revealing a beneficial relationship between long-term economic growth, AI, financial development, and LCF. On the contrary, urbanization, the digital economy, and GDP growth in the near future are detrimental to LCF. It is anticipated that financial growth will supply the capital required to invest in sustainable innovations that will boost industrial operations. Similarly, strong advancements in AI coupled with green growth stimulate the establishment of fresh ideas and the implementation of sustainable habits by promoting competitiveness and granting access to the latest technologies. The DKSE, AMG, and CCEMG tests, which corroborate the outcomes of the MMQR, add to the results' robustness. Furthermore, significant one-way causal linkages between LGDP, LGDP2, LAI, LFD, LDGE, LURBA, and LLCF were found by the D-H Causality analyses. These links highlight how the G-7 region's environmental sustainability dynamics are influenced by shifts in economic activity, advances in artificial intelligence, digital technology, urbanization, and financial expansion. As a result, the analysis provides several policy recommendations that, when paired with green development, improvements in technology, and practical urban infrastructure, ought to support a healthy environment in the selected region.

In order to tackle the U-shaped correlation between income and load capacity factor in the G-7 region, strategies must be developed to ensure both environmental sustainability and GDP expansion. As affluence increases, it is important to enforce more stringent rules on pollution and resource utilization in order to reduce the destructive effects on environmental sustainability. Providing subsidies and tax incentives to promote green technology and sustainable practices can effectively reduce environmental deterioration in the early phases of economic development. Moreover, allocating resources towards education and awareness initiatives might foster sustainable customer behavior. With the ongoing increase in wealth, it is imperative to redirect policy toward the promotion of sophisticated, clean technology and renewable energy sources. This will guarantee that rising income levels result in enhanced environmental consequences. Promoting corporate accountability and incorporating sustainability indicators into financial reporting may effectively propel organizations toward adopting more environmentally friendly practices. Collaborating and exchanging ideas between G-7 countries can further improve the efficacy of these initiatives.

To promote environmental sustainability in the Group Seven territories, policies should prioritize the integration of financial development and AI innovation into environmental strategies. Governments should prioritize the provision of financing and support for AI-driven technologies that facilitate the transition to renewable energy, optimize resource utilization, and improve environmental monitoring. Innovation and adoption can be stimulated by incentives for private sector investments in ecological AI solutions. Concurrently, financial policies should promote sustainable investment portfolios and green bonds, guaranteeing that financial development is consistent with sustainability objectives. Transparency and effectiveness will be guaranteed by the establishment of distinct standards and metrics for assessing the environmental impact of financial investments and AI. Fostering collaboration among environmental organizations, financial institutions, and tech developers, as well as promoting public-private partnerships, can facilitate the integration of AI-driven sustainability initiatives. Furthermore, policies should promote the creation of financial instruments that facilitate projects that generate substantial environmental benefits, thereby ensuring that financial growth is consistent with sustainable outcomes. The potential of AI and financial development can be leveraged by the G-7 countries to improve the green ecosystem through the implementation of these measures.

Policies should concentrate on sustainable development techniques in order to mitigate the negative consequences of the urban population and the rise of the digital economy on the LCF in the G-7 area. Encourage the IT industry to adopt energy-efficient practices and technology in order to lessen its environmental impact on the digital economy. Incorporate green data center guidelines and incentives and encourage the use of clean power sources in digital infrastructure. To mitigate the ecological impact of urbanization, give priority to smart city design that includes green infrastructure and effective land use. Regulations should be strengthened to guarantee that stringent environmental impact assessments and sustainability initiatives coincide with urban growth. Invest in green building techniques and public transportation to lessen the total demand for natural resources. Enforce stricter zoning regulations to safeguard natural regions and encourage mixed-use constructions that lessen the need for sprawling metropolitan areas. Through the integration of these measures, the G-7 nations may alleviate the detrimental impacts of urbanization and the rise of the digital economy on environmental sustainability, guaranteeing that technological and economic progress does not come at the price of ecological well-being.

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