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How G-7 countries are paving the way for net-zero emissions through energy efficient ecosystem?

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ABSTRACT

Given the relevance of the most burning issues across the globe, it is time to take action regarding the recovery of environmental issues such as global warming and climate change. Concerning inconsistencies and gaps in the prevailing literature, this study aims to investigate the role energy efficiency played in the energy related greenhouse gas emissions. With the advancement in the technological innovation, the importance of digitalization and environmental related technological innovation. Based on the economic importance of the Group of Seven (G7) economies, this study examined the connection of these variables in the mentioned group economies throughout 1990–2020. Employing advanced panel econometric approaches, the study found that prevalence of slope heterogeneity, cross-section dependence, and the existence of long-run equilibrium relationship. Due to non-linear data properties, the study uses non-parametric (method of moment quantile regression) technique. The results suggest the progressive role of energy efficiency, digitalization, and environmental related innovations on the environmental sustainability. These are substantial factors of sustainability as they significantly reduce the energy-related greenhouse gas emissions. On the contrary, economic growth is a significant driver of energy related greenhouse gas emissions. The results are robust and their causal linkage is also explored. This study suggests the increased investment and encouragement of energy efficiency, digitalization, and environmental related technological innovation in the G7 economies to pave the way for net zero emissions.

1. Introduction

The rise of globalization has greatly heightened economic expansion, exclusively in the world's developed economies. The fast pacing global economy has led to enormous consumption of energy and non-renewable resources that have escalated energy-related emissions worldwide (Zhu et al., 2022). Climate change and environmental degradation have become critical issues that have garnered the world for research (Zhao et al., 2022a). Supplementary, the unfavorable influence of environmental degradation on climate and human interaction with population transformation in which energy is a fundamental input for production and consumption purposes has raised the emissions levels, which has prompted nations and international organizations to come forward for a collective global solution (Polloni-Silva et al., 2021; JinRu and Qamruzzaman, 2022). Therefore, the present research focuses on assessing the determinants of energy-related emissions with the inclusion of digitalization. The policies of these economies and actions toward a low-carbon economy are important at the international level (Climate Transparency, 2018). The particular reason is that the economic size of G7, tech advancement and leadership, and their international coalitions play a special part in policy protocols and efficacious strategies for the sustainability of the world (Khan et al., 2020).

The G7 is the intergovernmental organization of developed economies with a noteworthy hold in global socio-economic and environmental policies. In Fig. 1 relative analysis of G7 regarding energy efficiency is illustrated. Italy ranks first among these seven developed countries, and the United Kingdom and Germany rank 2nd and 3rd, respectively. Despite this fact, in general, these were the top most energy-efficient economies with significant improvements in energy policies. Fig. 2 presents the comparative analysis of digitalization and

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innovation of G7. It can be seen that digitalization has peaked in all developed economies;however, improvement in environmentally related technologies is still required because innovation in environmental technologies is pertinent for achieving climate goals. The G7 economies have an imperative role in realizing climate action targets since they acquire almost 60% of the world's wealth and nearly 50% of GDP (Fig. 4), with practically huge contributions to energy-related emissions (Fig. 3) globally.

In the extant literature, several factors significantly affect carbon emissions; however, energy-related emissions also have a substantial relationship with the economic and environmental factors which the present study intends to determine. Therefore, the study aims to accomplish the succeeding objectives. First, the study examines the influence of digitalization on energy-related emissions. Second, the nexus between energy efficiency, environmental-related technologies, and energy-related emissions is analyzed. Third, the role of economic growth on energy-related emissions is assessed. To accomplish these, the study utilizes GHGENER as energy-related emissions, DEINOV as development in environmentally related technology, DIGIT as Digitalization, ENEREF as energy efficiency, and GDP. GHGENER, DEINOV, and DIGIT are obtained from the OECD, while GDP and ENEREF are obtained from the World Bank. The data span of these variables is from 1990 to 2020 for the 'Group of Seven countries. The authors employed innovative econometric approaches to examine the long-run associations and causal relationships between the study factors. The complete detail of the methodology is elaborated in Section 3 of the manuscript.

Based on the research objectives, the motivation behind the study is to examine the Impact of energy efficiency, Digitalization, and environmental technologies on GHGENER emissions for accomplishing zero emissions through an energy-efficient environment in G7 countries. The G7 are the global leaders that substantially impact the global economy. Their increased practice of fossil energy and development have increased harmful emissions. The study tends to hold significant economic and environmental importance in this regard. The novel findings for the G7 economies emphasize promoting a digital economy for an eco-friendly environment that will enable energy efficiency and conservation. Further, encouraging energy efficiency, digitalization, and improving environmental technology advancement supports environmental quality, which the estimation results have validated. Therefore, the study findings gave novel results for a sustainable environment, especially in the G7 economies.

The research provides significant contributions to the pragmatic literature in the following manner. The study's primary contribution is pioneering research in estimating the role of digitalization besides energy efficiency in the G7 economies. Previously, JinRu and Qamruzzaman (2022) explored the role of energy efficiency and environmental technologies with institutional quality with novel results. However, the current study incorporates the novel Impact of Digitalization alongside energy efficiency and environmental technology for net zero emissions ecosystems in G7, which is a significant novel distribution. The literature on digitalization is scarce, but a few studies (Ma et al., 2022; Puskarskij et al., 2022) recently scrutinized the role of digitalization in other economies, ignoring G7. Therefore, the present study empirically scrutinizes the role of digitalization and energy efficiency on GHGENER emissions and theoretically extends the debate on digitalization for improving environmental eminence. The implementation of the digital economy increases energy conservation and helps decarbonize the industrial economy, which is important in terms of the environment (Zhao et al., 2022b). Also, the rise of the digital economy has forced researchers, scholars, and environmentalists to pay attention to this. Second, the study employs econometric approaches to investigate the G7 economies with updated data with the longest period from 1990 to 2020 for zero emission through energy-efficient digital systems. The study uses MMQ regressions (since non-normal information is efficiently estimated), and Boostrap Quantile regressions for robustness (as they are non-parametric regressions that are estimated by re-sampling the original sample and then determining the values for each quantile for efficient estimates) and first time examines the causality analysis for the nexus of digitalization, energy efficiency, and environmental technologies with energy-related emissions in G7 simultaneously. Hence, the present study is a valid and new input to the empirical literature.

After the evocative introduction, the remaining manuscript is organized as follows. Section 2 represents the review of the relevant literature for research analysis. Section 3 documents the data, model, and methodology of the study. Section 4 briefs on the results and their economic interpretation. In addition, Lastly, Section 5 is about the conclusion and policy implications.

2. Literature review

This manuscript segment deals with empirical evidence related to the study factors, their relationships, and aspects that shed light on assessing the critical analysis.

2.1. Impact of economic growth on energy-related emissions

The decoupling effect is observed in assessing economic growth and environmental problems. In the prevailing literature on growth and emissions nexus, there are plenty of studies that confirm that economic

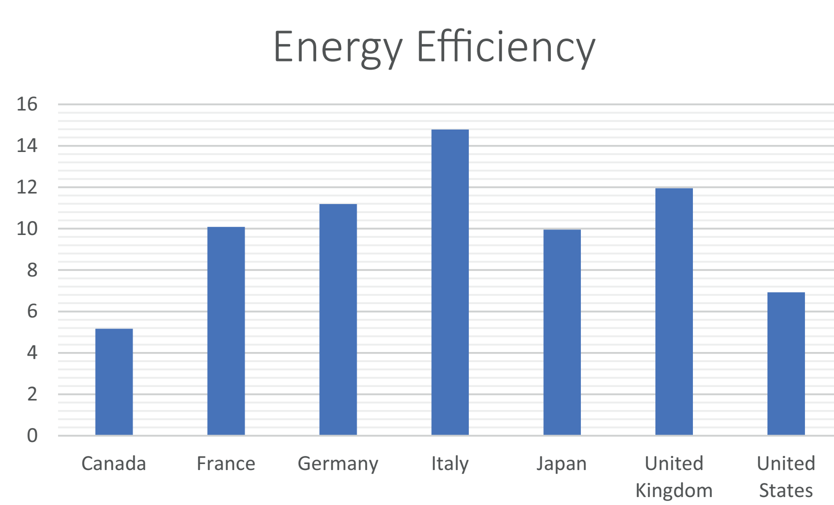

Fig. 1. Energy efficiency.

growth has a substantial influence on escalating carbon emissions. Wang and Zhao (2015) inspected the significant Impact between economic growth and carbon emissions. However, the influence in developing regions was greater than the others. Wang et al. (2017a) examined the decoupling effect in China. The study employed Log Mean Divisia Index Method and the empirical findings demonstrated that energy-related emissions (GHGENER) and economic growth substantially impact them. Because energy substantially offsets the Impact of economic growth on emissions (Hamilton and Turton, 2002). To scrutinize the determinants of energy-related emissions, STIRPAT and IPAT identity is applied. Hence, Wang et al. (2013) employed an extended version of STIRPAT and IPAT for GHGENER emissions factors. The results demonstrated that economic growth is a major contributor to GHGENER emissions. Later in another study GDP was found to be a significant contributor to GHGENER emissions (Wang et al., 2017b). Recently, Qing et al. (2022) examined the BRICS economies for growth and emissions nexus from 2000 to 2019. The study applied MMQ regressions which showed a significant impact between GDP and GHGENER emissions. Yang et al. (2021) analyzed the role of GDP on Energy-related emissions in China. The pragmatic conclusions demonstrated that GDP and GHGENER are correlated to each other. But then again suggested that innovations in energy efficiency are prolific in reducing GHGENER emissions. The improvement in technology for energy efficiency and reducing fossil energy leads to an impactful decrease in GHGENER emissions in the country. In the novel case study of Brazilian states, Polloni-Silva et al. (2021) examined the growth and emissions relationship employing the STIRPAT model. The empirical analysis depicted that GDP has a noteworthy impact on GHGENER emissions. Additionally, the following strand of literature also validated the positive Impact between GDP and GHGENER emissions in diverse economies (Raihan and Tuspekova, 2022; Raihan et al., 2022; Raihan and Tuspekova, 2022a; Su et al., 2020; Wiedenhofer et al., 2020; Fang et al., 2019; Lin and Raza, 2019; Dong et al., 2019). For causality analysis, (Esso and Keho, 2016; Khan et al., 2022a) showed causal associations in their findings.

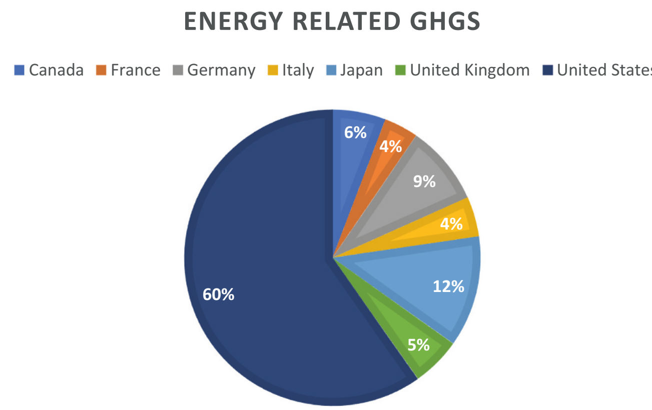

Fig. 3. Greenhouse gases from energy-related activities.

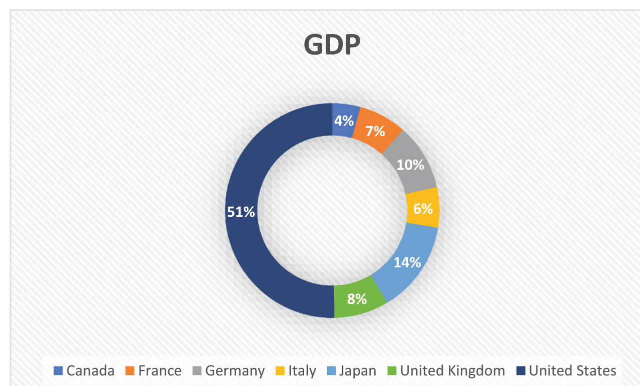

Fig. 4. Average GDP of G7 economies.

2.2. Nexus between environmental innovation, energy efficiency, digitalization, and energy-related emissions

Environmental-related technologies have a significant influence on limiting carbon emissions (Zheng et al., 2022). Hussain et al. (2022) investigated the influential Impact of environmentally related technologies (DEINOV) alongside the presence of renewable energy in plummeting GHGENER emissions in the case of E7 economies from 1990 to 2016. The findings suggest that DEINOV plays a crucial role in enhancing environmental quality. Hassan et al. (2022) examined the association between environmental-related technologies and energy-related emissions and determined a significant relationship in the abatement of GHGENER emissions. DEINOV aid in maintaining a sustainable environment by mitigating pollution levels and enhancing the quality of the environment (Hussain and Dogan, 2021). Similarly, Ghazouani et al. (2021); Khan et al. (2022) emphasized that environmental-related technology significantly helps enhance

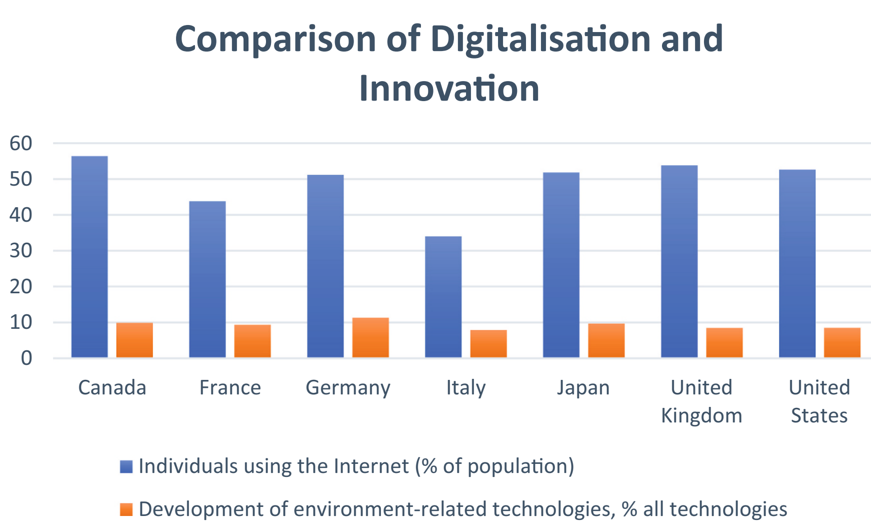

Fig. 2. Digitalization and innovation.

environmental quality by reducing pollution in Canadian and European Economies. In another recent analysis, Paramati et al. (2022) analyzed the OECD economies from 1990 to 2014. The empirical results demonstrated that environmentally related technologies encourage energy efficiency in the country, which is fruitful in mitigating the deterioration of the environment by limiting emissions.

Energy efficiency is known to have a negative influence on controlling emissions. Qing et al. (2022) discovered the mitigating role of energy efficiency in GHGENER emissions in BRICS nations. The (MM) Quantile regressions substantially showed significant relationships in all Quantiles depicting energy efficiency reduced emission levels. In the case of developing countries, structural changes increase the level of pollution in the country from 1990 to 2016. Therefore, energy efficiency is imperative in limiting GHGENER emissions in those economies (Mirza et al., 2022). In another research using the ARDL approach in China, Lei et al. (2022) observed that positive surprises in energy efficiency substantially reduce GHG emissions, indicating a negative impact between energy efficiency and GHGENER emissions. Likewise, Hassan et al. (2022) evaluated the role of energy efficiency in mitigating GHG emissions in high OECD economies. Similar negative associations were discovered in the shipbuilding case (Vakili et al., 2022). In a comparative study of developing and developed economies, Mahapatra and Irfan (2021) determined asymmetric effects between the energy and emissions nexus. The positive surprise of energy efficiency decreases emissions while the negative shock increases the GHGENER emissions in the long run. For causal analysis, Akdag and Yıldırım (2020) observed a significant causal relationship between energy efficiency and GHGENER emissions.

The Impact of the digital economy depends on the country-to-country level of digitalization. The empirical results from Dong et al. (2022) demonstrate that digitalization reduces the intensity of emissions, but per capita emission levels tend to increase. In a large body of environmental literature, studies on digitalization and emissions nexus are quite rare. However, the following research elaborates on the negative relationship between digitalization and GHGENER emissions. Lately, Ma et al. (2022) assessed the Impact of Digitalization on energy GHG emissions in the case of China from 2006 to 2017. The empirical results depicted that variables under consideration have long-run associations, indicating that digitalization significantly eliminates energy emissions. Digitalization enables clean energy and promotes energy efficiency, leading to sustainable development goals (Hellemans et al., 2022; Çelik et al., 2022). Likewise, Puskarskij et al. (2022) examined that digitalization enhances energy efficiency, giving momentous insights that help achieve carbon neutrality targets. In an innovative study, Zhu et al. (2022) emphasized the improvement in the digital economy in terms of environmental enhancement. The results depicted that digitalization has a dampening effect on GHGENER emissions. Wen et al. (2021) also observed that digitalization in the industrial sector limits large-scale production that emits harmful emissions and encourages product innovation, enhancing environmental quality. In the case of BRICS economies, Chen (2022) investigated the negative Impact of Digitalization and GHGENER emissions with significant long-run associations.

3. Theoretical framework and methodology

3.1. Theoretical framework and model construction

The theoretical notion through which economic growth (GDP), energy efficiency (ENEREF), Digitalization (DIGIT), and development of environmental related innovations (DEINOV) affect the energy related greenhouse gas emissions (GHGENER) is discussed in this section. Affordability encourages activities and industrial pollution, which creates carbon dioxide emissions, and could exacerbate the danger of climate change (Liu et al., 2021; Cheng et al., 2019). Due to the increasing production of greenhouse gases, economic growth also enables consumers to acquire ecologically dangerous items such as automobiles, microwaves, exhausts and other pollution intensive goods (He et al., 2019; Wu and Zhao, 2018; Ma et al., 2013). More specifically, higher economic growth can increase GHG emissions by using non-renewable energy resources. In other words, the higher use of traditional fossil fuels could lead the industrial sector to run, further boosting income circulation and encouraging per capita income. However, the higher level of per capita income simultaneously increases the savings and investment level in the industrial sector, which further surges the energy demand. Consequently, the burning of fossil fuel more fossil fuel, as seen in the example of USA and China (the highest energy importers and pollution emitters in the world) could lead to higher GHG emissions and causes the issue of climate change and global warming. From the discussion, this study assumes the positive influence of GDP on GHGENER, given as: $\delta_1 = \frac{GHGENER_{it}}{GDP_{it}} > 0$.

With the emergence of technology, each region tends to multiply its growth by using a minimum of its resources. Similarly, with increasing environmental concerns such as climate change and global warming, economies are now well-known for the destruction caused by the extensive of energy intensive products and services. In this respect, scholars and policy-makers are forcing the development of energy efficiency, digitalization, and development of environmental related innovations through technological advancement (Shahzad et al., 2021; Zhao et al., 2022c). Apart from the economic benefits of these indicators, they could play a vital role in the sustainability of environment via directly reducing emissions and other pollutions level (Lei et al., 2022; Li et al., 2021; Khan et al., 2021). Generally, power plants use fossil fuels like coal and natural gas. The combustion of fossil fuels results in the emission of GHGs like carbon dioxide, which contributes to climate change. Nevertheless, energy efficiency has several environmental advantages. It significantly decreases greenhouse gas emissions directly from fossil fuel burning or consumption and indirectly through power production. Based on the above discussion, this study assumes that ENEREF could lower GHGENER, given as: $\delta_2 = \frac{GHGENER_{it}}{ENEREF_{it}} < 0$. Currently, digital technologies are being employed to address bigger challenges, such as the sustainability of the environment. Data analytics, sensors, networked devices, and other digital technologies are altering energy usage and consumption across the economy. Additionally, these technologies provide new options to improve energy use and reduce energy related GHG emissions. Such adverse Impact of Digitalization is evident in the recent literature strand (see e.g., Wen et al., 2021; Ramos-Meza et al., 2021), which could be expressed as $\delta_3 = \frac{GHGENER_{it}}{DIGIT_{it}} < 0$. Development of environmental-related innovation necessitates modifying corporate systems and procedures, boosting productivity, decreasing GHG emissions, and decreasing resource costs. In addition, it eliminates dangerous inputs, improves the manufacturing process, and mitigates the adverse consequences of production output. Examples of existing environmental-related innovations include energy recovery from solid waste, renewable energy sources, waste utilization for material recovery, eco-products, fertilizer generation from wastewater, and different managerial methods (Eryigit and Özcüre, 2015). The literature is extensive regarding the evidence of a progressive role of DEINOV in environmental sustainability (Amin et al., 2022; Puertas and Marti, 2021). Such studies claimed that DEINOV significantly the level of GHG in the country, which forces this study to assume: $\delta_3 = \frac{GHGENER_{it}}{DEINOV_{it}} < 0$. For reference, please see Fig. 5 for graphical representation of the theoretical framework.

Based on the theoretical notion and literature, this study aims to examine the nexus of GDP, ENEREF, DIGIT, and DEINOV, with GHGENER. Following the study of Khan et al. (2021) and Lei et al. (2022), this study develops the following model for empirical analysis:

$$GHGENER_{it} = f(GDP_{it}, ENEREF_{it}, DIGIT_{it}, DEINOV_{it})$$

For the clarity of readers and empirical estimations, the above model

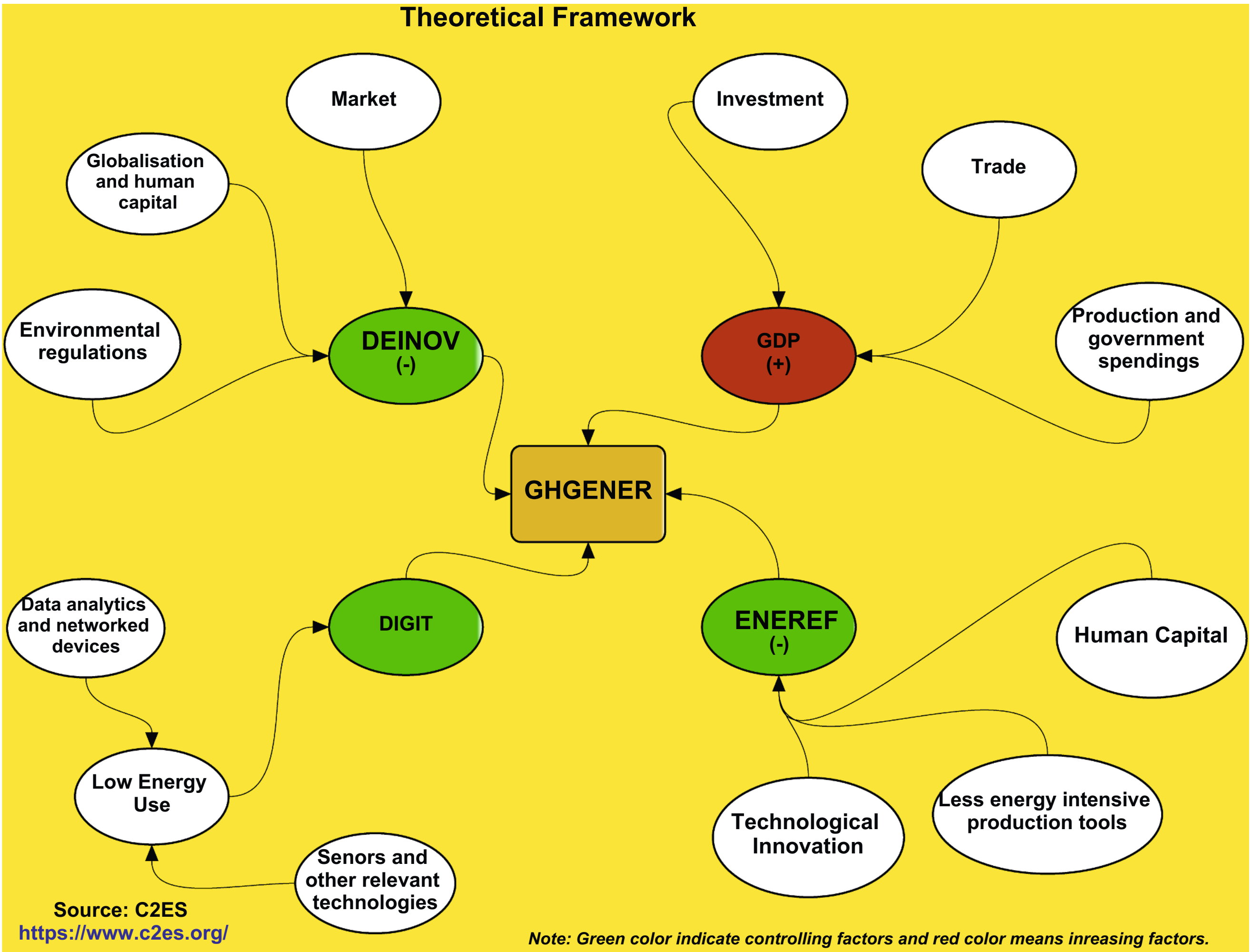

Fig. 5. Theoretical link via flowchart.

can be transformed into a regression model, given as:

$$GHGENER_{it} = \gamma_0 + \delta_1 GDP_{it} + \delta_2 ENEREF_{it} + \delta_3 DIGIT_{it} + \delta_4 DEINOV_{it} + e_{it} \quad (1)$$

where, γ_0 captures the model's intercept, $\delta's$ reflects the slopes of variables, e_{it} Indicates the model's random error, and the subscript i and t indicate the cross-sections (G7 in this case) and time-series (1990–2020), respectively. Data for these variables are obtained from various reliable sources, which include OECD[1] and the World Bank.[2] Nonetheless, there are several developed and developing economies. Yet, the G7 is the informal bloc of highly industrialized economies that aims to cross-cut the burning issues in the world and play the catalyst. Environmental degradation and climate change have been the most debated issue for the last few (three in particular) decades. Therefore, it is critical to examine these economies, which could take serious actions against these burning issues and lead the world from the front.

3.2. Estimation strategy

This research explores descriptive statistics for researched variables to provide a comprehensive overview of panel data. In particular, descriptive analytics covers the mean, median, and range statistics, the latter containing the lowest and highest data properties. This research also investigates the variable's standard deviation, demonstrating the time variable's volatility by demonstrating the data's divergence from the mean. In addition, two normalcy metrics are performed to analyze the data's distributive properties. Specifically, skewness and Kurtosis are employed to verify whether a variable's distribution meets the normalization criteria. Despite the fact that Skewness and Kurtosis provide genuine information on the variable's dispersion. However, this approach tackles the issue of normality in more detail. This study used the Jarque and Bera (1987) normality assumption, which assesses skewness and excess Kurtosis and assumes their value equal to zero, hence confirming the null hypothesis that the normal distribution exists in a given dataset. The following is Jarque-Bera's mathematical expression for normality statistics:

$$JB = N.\frac{1}{6}\left(S^2 + \frac{(K-3)^2}{4}\right) \quad (2)$$

Since this research focuses on panel data; accordingly, panel data techniques are appropriate to employ. The first phase of this panel inquiry is to evaluate the Slope heterogeneity and Cross-section Dependence of the selected Panel data. In certain areas, panelist nations may

[1] Data for GHGENER, DIGIT [Individuals using the Internet (% of population)], and DEINOV (% all technologies) is obtained from the OECD (2022) website, Available at: https://stats.oecd.org/.

[2] Data for GDP (constant US dollars 2015) and ENEREF [GDP per unit of energy use (constant 2017 PPP $ per kg of oil equivalent)] from the World Development Indicators of the World Bank (2022), available at: https://databank.worldbank.org/source/world-development-indicators#.

have both similarities and distinctions. However, the similar characteristics of countries may lead to inaccurate forecasts in econometric research, particularly in panel estimations (Wei et al., 2022). Accordingly, it is essential to assess if the G7 economies have similar or distinct characteristics. In this instance, the slope coefficient homogeneity test of Pesaran and Yamagata (2008) was used to examine coefficients that have been comparable to the null hypotheses: slope coefficients are homogeneous. The basic formulas for the aforesaid specification are as follows:

$$\widehat{\Delta}_{SCH} = (N)^{1/2}(2k)^{-1/2}\left(\frac{1}{N}\acute{\mathrm{S}} - \mathrm{K}\right) \tag{3}$$

$$\widehat{\Delta}_{ASCH} = (N)^{1/2}\left(\frac{2K(T-K-1)}{T+1}\right)^{-1/2}\left(\frac{1}{N}\acute{\mathrm{S}} - 2\mathrm{K}\right) \tag{4}$$

where $\widehat{\Delta}_{SCH}$ reflects the slope coefficient homogeneity and $\widehat{\Delta}_{ASCH}$ symbolizes the slope coefficient homogeneity after modification or adjustment.

In today's globalized market, various factors may increase a country's dependence on the remainder of the world, such that a change in a parameter in one region may have repercussions in another economy or region. Yet, ignoring cross-sectional dependence may lead to erroneous and misleading findings (Wei et al., 2022). Therefore, we utilized Pesaran's (2004) test of cross-section dependency to assess cross-section reliance across the G7 countries. The following is the mathematical representation of the priorly described test, which takes independent cross-sections as the null hypothesis:

$$\mathrm{CD}_{Test} = \sqrt{\frac{2T}{N(N-1)}}\sum_{i=1}^{N-1}\sum_{k=1+i}^{N} T_{ik} \tag{5}$$

Due to the commonality of panel data challenges, i.e. cross-section dependence and slope coefficient heterogeneity, an appropriate unit root estimate method is utilized to circumvent these problems. This study employed the cross-sectional IPS (i.e., CIPS) test constructed by Pesaran (2007), which is significantly robust as compared to the existing unit root estimators such as Dickey-Fuller, Augmented Dickey-Fuller, Levin, Lin, and Chu, etc. Pesaran (2006) originally conceived a factor model to analyze inexplicable cross-sectional means for cross-sectional dependence. By employing the same methodologies, Pesaran (2007) manages to combine the average and first differed cross-section lags into the Augmented Dickey-Fuller linear expression. This methodology allowed cross-sectional dependence irrespective of the imbalance of the panel (T > N or N > T). Using the following equation, we could calculate the CIPS statistics:

$$CIPS = N^{-1}\sum_{i=1}^{N} CADF_i \tag{6}$$

In instances the Pesaran (2007) test assumes the persistence of unit root in a panel time series.

Considering that all relevant factors are stationary, this enables the determination of the long-term equilibrium relationship between the research variables. Accordingly, to the diagnostic tests' estimates, indicate heterogeneity of slope coefficients and confirm cross-sectional reliance. Therefore, this study employs an adequate empirical method that accounts for the aforementioned barriers. Specifically, Westerlund's (2007) method for error correction is implemented. This test supposes the error correction component has a value of zero — which is regarded as the null prediction of the under-discussion approach. This assessment is particularly effective because it takes into consideration both the group mean stats, i.e., $G_\tau = \frac{1}{N}\sum_{i=1}^{N}\frac{\widehat{\alpha}_i}{S.E\widehat{\alpha}_i}$, and $G_a = \frac{1}{N}\sum_{i=1}^{N}\frac{T\widehat{\alpha}_i}{\widehat{\alpha}_i(1)}$, and the panel stats, i.e., $P_\tau = \frac{\widehat{\alpha}}{S.E(\widehat{\alpha})}$, and $P_a = T.\widehat{\alpha}$.

Since the investigated variables expressed stationarity, one of the basic requirements for calculating long-run elasticities, and also contains the characteristics of long-run cointegration; hence, the long-run elasticities can be calculated. Subsequently, the ongoing study takes into account the non-symmetric data distribution, entailing the use of a novel Method of Moment Quantile Regression (MMQR) strategy. Although there are several econometric approaches available, which could identify the long run coefficients, such as panel fully modified ordinary lear square, dynamic ordinary least square, generalized method of moment, among others. However, these methods are limited in terms of accounting for the non-linearity, which could provide inefficient estimates.

Koenker and Bassett Jr (1978) described the quantile regression method for assessing the mean dependence and conditional variance for reducing the nonlinearity issues. Machado and Silva (2019) developed the MMQR technique for assessing the dispersion of quantile estimates based on the latter methodology (Sarkodie and Strezov, 2018). The sophisticated expression for the conditional location-scale variance $Q_y(\tau|R)$ is as follows:

$$Y_{it} = \alpha_i + \beta R_{it} + (\gamma_i + \rho\acute{Z}_{it})\mu_{it} \tag{7}$$

In the prior expression, the probability representation $p(\gamma_i + \rho\acute{Z}_{it} > 0)$ is equal to one, whereas α, β, γ, and ρ represent the parameters that this study prefers to anticipate. The subscript *"i"* denotes the fixed effect stipulated by the characteristics α_i and γ_i which would be restricted to the values $i = 1, 2, \dots, n$. Here, the distinctive feature of R, symbolized by Z, is the k-vector, while the variability is denoted by vector "$\imath$."

$$Z_\imath = Z_\imath(R), \imath = 1, 2, \dots, k \tag{8}$$

From the equation, it must be noted that R_{it} is distributed identically and independently for the total fixed *i* and time *(t)*, which is in itself orthogonal to both *t* and *i* (Machado and Silva, 2019). Consequently, the outer components and reserves are both steady. On the basis of the preceding explanation, the research model as discussed and presented earlier, may be modified as follows:

$$Q_y(\tau|R_{it}) = (\alpha_i + \gamma_i q(\tau)) + \beta R_{it} + \rho\acute{Z}_{it}q(\tau) \tag{9}$$

In the customized research framework, the set of independent variables, which contains GDP, ENEREF, DIGIT, and DEINOV, has been expanded R_{it}. Each of the mentioned variables is transformed into natural logarithm, rendering them unitless, and to present their estimated outcomes as a percentage. Furthermore, R_{it} represents the quantile dissemination of the predictor variables, as implied by Y_{it}, and is presumed to be GHGENER in this study, which also depends on the quantile position. Furthermore, the expression $-\alpha_i(\tau) \equiv \alpha_i + \gamma_i q(\tau)$ reflects the scalar element that produces the fixed effect of τ quantiles on i however, these quantiles have no effect on the intercept. Several more outcomes are susceptible to change owing to the structural independence of the specifications. Lastly, $q(\tau)$ symbolizes the $\tau - th$ quantile sample, which are $Q^{0.25}$, $Q^{0.50}$, $Q^{0.75}$, and $Q^{0.90}$ in this study. Therefore, the quantile formula utilized in this study is as follows:

$$min_q \sum_i \sum_t \theta_\tau(R_{it} - (\gamma_i + \rho\acute{Z}_{it})q) \tag{10}$$

where $\theta_\tau(A) = (\tau - 1)\,AI\{A \le 0\} + TAI\{A > 0\}$ denotes the feature for testing.

Nonetheless, the MMQR method provides accurate projections at a certain location and scale by displaying quantile values. However, this research concentrates on determining the reliability of the model. Hence, the present research used the Bootstrap Quantile Regression (BSQR) technique. The BSQR approach is an interstitial technique for analyzing confidence intervals and the significance of statistics. The benefit of these limitations is that they resample the information to get quantifiable information while avoiding the asymptotically normal sample distribution restriction (Efron and Tibshirani, 1994). To be more precise, the BSQR employs algorithmic capabilities for estimating the sample distribution of the assessed model. In addition, this methodology provides more effective estimating methods and empirical results (Efron and Tibshirani, 1994).

Aside from the long-term estimator and its robustness, the purpose of this article is to analyze the causation link between GHGENER and regressors, since previous estimate methods failed to show a causality relationship between the studied variables. This work employs the panel Granger causality test developed by Dumitrescu and Hurlin (2012), which is more effective at overcoming the aforementioned challenges with panel data, including cross-section dependency and slope heterogeneity.

4. Results and discussions

This section elaborates on the results estimated using the methodology stated in Section 3 of the manuscript. The pre-estimation statistics, long-run assessment, regression scrutiny, and causality analysis are interpreted chronologically in the following manner.

4.1. Pre-estimation diagnostics

Starting with descriptive diagnostics statistics in Table 1. The mean and median values of all the study variables are almost similar to each other, demonstrating the balancing point of the data. The positive signs of the average and mean values depict the positive growth of study variables over time. The variables' standard deviations illustrate the information's volatility and how much they deviate from their mean position. Their statistical values illustrate the data spread. The numerical values of skewness and kurtosis show the symmetry and peakedness of the distribution. However, ENEREF, DIGIT, and DEINOV are negatively skewed, while GHGENER and GDP are positively skewed, as mentioned in the Table below. The Jarque Bera shows the non-normality of the distribution and the probability statistics show significant findings.

4.2. Heterogeneity and cross-sectional dependence

Next, after the analysis of the successful descriptive diagnostics leads to applying Slope Heterogeneity and Cross-Sectional dependence tests on the variables. In a cross-sectional or panel data analysis, a diverse range of underlying aspects have a social, financial, or technical impact on the study factors. Therefore, slope heterogeneity and cross-sectional dependence tests are applied before the beginning of the estimation process. In Table 2 beneath, the results from slope heterogeneity are presented. The statistical values of the slope coefficient test are significant at a 1% level of significance, thereby rejecting the null hypothesis of homogeneity. The findings demonstrate that there is the existence of heterogeneity among the variables, which leads to the analysis of the cross-sectional dependence of variables.

The results from cross-sectional dependence findings are all statistically significant at a 1% level of significance. The asterisks on the coefficients in Table 3 depict that the null hypothesis of no interdependence is rejected, indicating that all variables are interrelated and cross-sectionally dependent. The general conclusion of the test is that all variables GHGENER, GDP, ENEREF, DIGIT, and DEINOV are cross-sectionally dependent in G7 countries.

Table 2
Slope heterogeneity.

Homogenous/Heterogeneous slope coefficient testing	
Test	Statistic
$\tilde{\Delta}$	20.984***
$\tilde{\Delta}^{\text{Ajusted}}$	22.913***

Note: Significance level is denoted by *** for 1%, ** for 5% and * for 10%.

Table 3
Cross-sectional dependence.

Cross-sectional dependence testing	
GHGENER	**GDP**
9.803***	23.455***
DIGIT	**ENEREF**
25.323***	23.523***
DEINOV	
23.606***	

Note: Significance level is denoted by *** for 1%, ** for 5% and * for 10%.

4.3. Unit root analysis and cointegration tests

Now the unit root analysis is held using Pesaran's (2007) CIPS test. The stationarity results are presented in Table 4. GHGENER and GDP showed significance at first difference while ENEREF, DIGIT, and DEINOV are statistically significant at a level with a 1% level of significance. Additionally, the negative coefficient values indicate the unit root's stronger existence. The significance of the results rejected the null hypothesis of no stationarity and led examine the variables' long-run association.

All the variables in root analysis possess the property of stationarity that forces us to assess the cointegration analysis. The study uses the Westerlund ECM Cointegration Test for that purpose. The test results in Table 5 show that the null hypothesis is of no cointegration. The significant *p*-values show the presence of long-run associations between the variables indicating ENEREF, DEINOV, GDP, and DIGIT are cointegrated

Table 4
Testing unit root.

Pesaran (2007) CIPS			
Variable	I(0)	I(1)	Level of integration
GHGENER	−2.516	−5.415***	I(1)
GDP	−1.904	−4.196***	I(1)
ENEREF	−3.102***	–	I(0)
DIGIT	−3.037**	–	I(0)
DEINOV	−3.857***	–	I(0)

Note: Significance level is denoted by *** for 1%, ** for 5% and * for 10%.

Table 1
Diagnostic tests and normality stats.

	GHGENER	GDP	ENEREF	DIGIT	DEINOV
Mean	5.912288	12.47180	0.973963	1.287627	0.947816
Median	5.766892	12.40003	0.980833	1.779596	0.972203
Maximum	6.799496	13.30048	1.218133	1.984527	1.187239
Minimum	5.481925	11.97023	0.625786	−1.755857	0.674861
Std. Dev.	0.385423	0.328406	0.156941	0.922636	0.134223
Skewness	1.317023	1.095849	−0.521112	−1.514445	−0.278807
Kurtosis	3.589488	3.554970	2.463774	4.206636	1.929501
Jarque-Bera	65.87479	46.21675	12.42115	96.11426	13.17283
Probability	0.000000	0.000000	0.002008	0.000000	0.001379

Table 5
Cointegration testing.

Westerlund ECM cointegration test			
Variable	Value	*Z*-value	*p*-value
G_t	−2.661	−1.756	0.040**
G_a	−8.758	0.417	0.662
P_t	−6.529	−1.778	0.038**
P_a	−7.630	−0.548	0.292

Note: Significance level is denoted by *** for 1%, ** for 5% and * for 10%.

with GHGENER emissions in G7 countries.

4.4. Method of moments quantile regression

The non-normality of the information pointed to applying the Method of Moments Quantile Regressions for investigating the determinants of energy-related emissions. The primary results are presented in Table 6 of the manuscript with the following possible variables interpretations. First, economic growth shows a significant association with GHGENER emissions in all quantiles with a positive relationship. The increase in the economic activity of an economy increases production, which significantly increases the harmful emissions related to energy and carbon negatively affecting the environment. The variable finding is consistent with (Qing et al., 2022; Raihan et al., 2022; Raihan and Tuspekova, 2022a; Polloni-Silva et al., 2021; Su et al., 2020; Wiedenhofer et al., 2020; Fang et al., 2019). That is, increasing GDP has substantially raised the levels of emissions. Second, energy efficiency is negatively associated with energy-related (GHGENER) emissions as the coefficients in all quantiles have a negative sign indicating an inverse association between ENEREF and GHGENER. The variable outcome is consistent with (Qing et al., 2022; Mirza et al., 2022; Lei et al., 2022). This states that an increase in energy efficiency promotes energy conservation that significantly decreases the emissions (GHGENER) in G7 economies. Third, the development of environmental-related technologies' is significant in the first quantile, as mentioned in Table 6 beneath, depicting that DEINOV has a consequential association with GHGENER emissions. However, the coefficient signs are negative in all quantiles, demonstrating that an increase in DEINOV helps decrease GHGENER emissions in G7. These are in line with the results of (Hussain et al., 2022; Hassan et al., 2022). Fourth, the role of digitalization has also shown significant findings with GHGENER emissions in G7 countries. The results depict that increasing digitalization decreases the level of GHGENER due to the existence of a negative association between DIGIT and GHGENER. The result is consistent with (Ma et al., 2022; Dong et al., 2022; Chen, 2022). It is signifying that promoting a digital economy increases efficient energy and mitigates GHGENER emissions in the country, enhancing a clean and sustainable environment. The graphical trend between ENEREF, DEINOV, GDP, and DIGIT with GHGENER emissions is illustrated in Fig. 6 of this section representing the research variables in all (MMQR) quantiles.

4.5. Robustness check - BSQR

The robustness of the model is analyzed with Bootstrap Quantile regressions (BSQR) in Table 7. The statistics of the tests show that the model applied is reliable and predicted significant and efficient results. The significant results are presented in the table, especially in Q (0.75) and Q (0.90). However, the coefficient signs showed positive but significant results. The graphical presentation of coefficients of all variables (in all quantiles) is illustrated in Fig. 7 of this section.

4.6. Causality analysis

The study employs the 'Dumitrescu-Hurlin Panel Causality' analysis to examine the causal association between dependent and independent variables for which variable impacts the who. The variable pairs GDP ≠ GHGENER, GHGENER ≠ GDP; ENEREF ≠ GHGENER, GHGENER ≠ ENEREF; and DEINOV ≠ GHGENER, GHGENER ≠ DEINOV showed bidirectional causality with each other with 1% and 10% levels of significance while DIGIT ≠ GHGENER and GHGENER ≠ DIGIT showed no significant causal association between them. The results indicate that economic growth and GHGENER emissions, energy efficiency and GHGENER emissions, and development in environmentally related technologies, and GHGENER emissions cause each other which is statistically illustrated in Table 8.

For general interpretation of the findings of causality analysis, the probability statistic results are in line with the outcomes of the following studies (Esso and Keho, 2016; Akdag and Yıldırım., 2020; Khan et al., 2022a). However, the causal association between DEINOV and DIGIT with GHENER is novel in the pragmatic body of knowledge and the findings contribute to the prevailing literature.

4.7. Empirics discussion

The above conversation provided the estimated results from the econometric approaches applied. The stepwise discussion of the outcomes demonstrates that the variables economic growth (GDP), energy efficiency (ENEREF), development of environmentally related technologies (DEINOV), and Digitalization (DIGIT) have a long-run and significant relationship with the energy-related emissions (GHGENER) in the G7 economies. Later the regression analysis demonstrated that the increasing economic growth due to increasing production activities increases the energy-related emissions in the country. Also, environmentally related technologies, energy efficiency, and digitalization proved to be significant contributors to controlling and limiting emissions. The digital economy increases energy efficiency that promotes environmental sustainability. While improving digitalization also increases the role of advancement in environmental technologies, which is substantial in limiting energy emissions.

Table 6
Primary results – MMQR.

Variable	Location	Scale	Quantiles			
			$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.90}$
GDP	1.058***	−0.051***	1.076***	1.034***	1.006***	0.990***
	[0.013]	[0.009]	[0.020]	[0.012]	[0.010]	[0.011]
ENEREF	−0.818***	0.111***	−0.857***	−0.765***	−0.704***	−0.670***
	[0.043]	[0.031]	[0.060]	[0.038]	[0.034]	[0.037]
DEINOV	−0.106*	0.046	−0.122*	−0.085	−0.059	−0.045
	[0.062]	[0.044]	[0.074]	[0.052]	[0.050]	[0.054]
DIGIT	−0.022**	0.002	−0.022**	−0.023***	−0.024***	−0.024***
	[0.009]	[0.007]	[0.011]	[0.008]	[0.007]	[0.008]
Constant	−6.359***	−0.553***	−6.554***	−6.098***	−5.791***	−5.622***
	[0.190]	[0.136]	[0.265]	[0.166]	[0.151]	[0.163]

Here, GHGENER is the dependent variable. Note: Significance level is denoted by *** for 1%, ** for 5% and * for 10%.

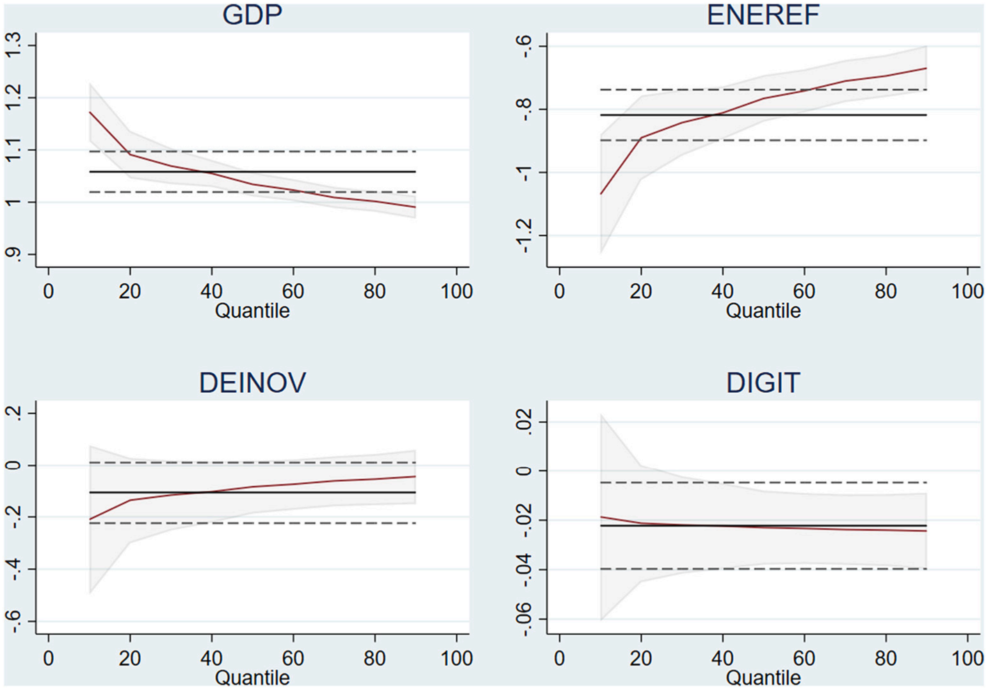

Fig. 6. Graphical depiction of the coefficients – MMQR.

Table 7
Robustness results – BSQR.

Variable	Quantiles			
	$Q_{0.25}$	$Q_{0.50}$	$Q_{0.75}$	$Q_{0.90}$
GDP	1.084***	1.044***	1.006***	0.999***
ENEREF	0.917***	0.800***	0.729***	0.732***
DEINOV	0.131	0.100	0.095**	0.056***
DIGIT	0.015	0.015	0.017***	0.031***
Constant	6.600***	6.191***	5.740***	5.653***

Here, GHGENER is the dependent variable. Note: Significance level is denoted by *** for 1%, ** for 5% and * for 10%.

The regression results are in line with the findings of the following strands of literature (Mirza et al., 2022; Lei et al., 2022; Hussain et al., 2022; Hassan et al., 2022; Ma et al., 2022; Dong et al., 2022; Chen, 2022; Qing et al., 2022; Raihan et al., 2022; Raihan and Tuspekova, 2022a; Polloni-Silva et al., 2021; Su et al., 2020; Wiedenhofer et al., 2020; Fang et al., 2019). Similarly, the causality analysis is consistent with (Esso and Keho, 2016; Akdag and Yıldırım., 2020; Khan et al., 2022a). In general, the association between digitalization, environmental technologies, energy efficiency, and energy-related emissions are novel findings in the case of G7 economies. The overall results hold significant economic and environmental significance. Therefore, pragmatic policies with reference to these findings can be structured to improve the economies' global performance economically and environmentally. The promotion of an integrated digital economy and innovation regarding eco-friendly practices for energy efficiency and a clean and green economy are resourceful in limiting emissions related to energy. The increasing energy usage led to energy-related emissions, which deteriorate the environment and affect the quality of life. The G7 are known to be the global leaders; their actions toward climate have a direct and indirect impact on their neighboring nations. Moreover, developing economies are suffering from the consequences of developed countries. Their increasing non-renewable consumption of energy and practices impacts the global economy. Therefore, proper and efficient strategies are required to sustain the economy and environment at the national and international levels.

5. Conclusion and policy implication

To sum up, the study examines the relationship between digitalization, economic growth, the development of environmental technologies, and energy efficiency on energy-related emissions. The findings are novel in terms of simultaneous assessment of the abovementioned variables in G7 countries. Although these factors have been extensively inspected, digitalization is overlooked. Therefore, the present research intends to investigate whether digitalization and energy efficiency are imperative for flooring net zero discharges through an efficient ecosystem. The study scrutinized the determinants of GHGENER emissions in G7 with innovative econometric techniques. The improvement of the digital economy is responsible for technological innovation, sinking poverty, and improving living standards, besides lowering carbon and energy emissions. On the other hand, as the findings suggest, energy efficiency, economic growth, and environmental technologies are substantial factors for controlling emissions to enhance the environment. The results were somehow consistent with a few prevailing studies. Overall, the connotation amid digitalization, environmental technologies, energy efficiency, and energy-related emissions provides novel findings in the case of G7 economies. Our study found that digitalization, energy efficiency, and innovations led to limited energy-related emissions. These are imperative for environmental quality and an important source of sustainable economic development and progression.

Grounded on the research findings, the following are some relevant policy implications that could transform the environmental economy. Technological development is significant for the environment and enhancement of industrial sectors. As a result, economic sustainability will surge. The eco-friendly innovation reduces harmful discharges and improves the deep integration of communities for the global economy. Governments should promote and focus on efficient resource utilization for innovative development. Furthermore, the improvement and development in the digital economy in terms of the environment must be endorsed. This is noteworthy in encouraging smart technologies alongside energy-efficient services to improve well-being. Moreover, it will intensify artificial intelligence for the protection of biodiversity and climate along with resource efficiency. It could change the world

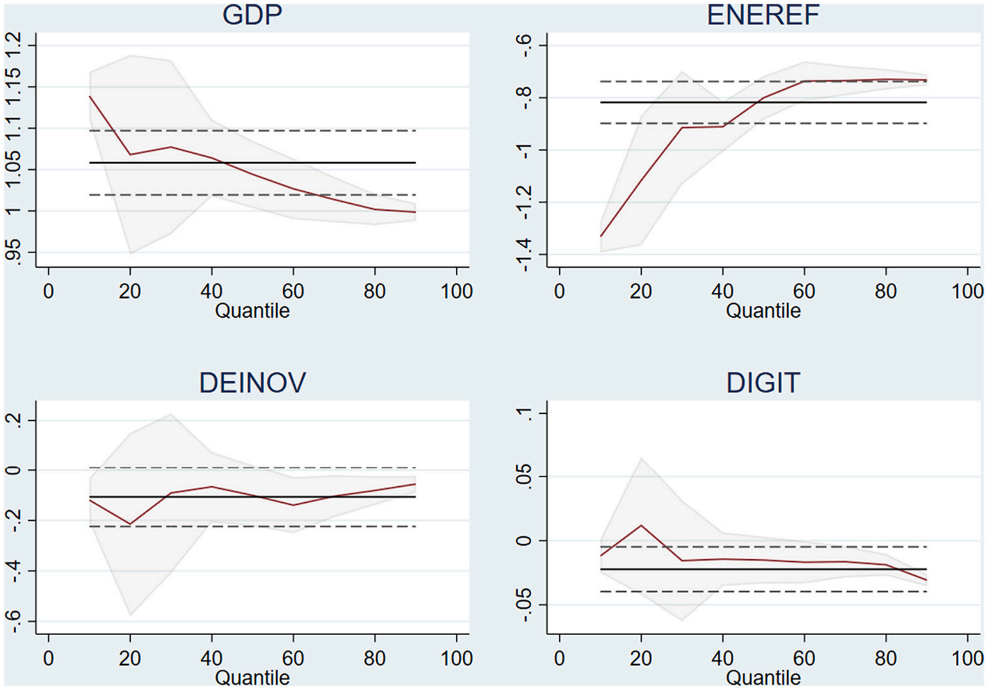

Fig. 7. Graphical depiction of the coefficients – BSQR.

Table 8
Panel causality test.

Dumitrescu-Hurlin panel causality			
H_0	$Wald_{Stats}$	$\overline{Z}_{stats}$	p − value
GDP ≠ GHGENER	5.40457***	7.04581	2.E-12
GHGENER ≠ **GDP**	2.18915*	1.80708	0.0707
ENERF ≠ GHGENER	3.37736***	3.74297	0.0002
GHGENER ≠ **ENEREF**	3.91651***	4.62139	4.E-06
DIGIT ≠ GHGENER	1.71600	1.03620	0.3001
GHGENER ≠ **DIGIT**	1.29483	0.35001	0.7263
DEINOV ≠ GHGENER	5.66669***	7.47286	8.E-14
GHGENER ≠ **DEINOV**	3.71621***	4.29505	2.E-05

Note: Significance level is denoted by *** for 1%, ** for 5% and * for 10%.

through ingenuity and innovation. In addition, developed countries must reduce the increased non-renewable consumption of energy and practices as they also impact the global economy, especially the developing and vulnerable countries that are facing floods and draughts due to severe side effects of climate. Consequently, appropriate and well-organized stratagems are obligatory for the sustainability of the economy and environment at the domestic at international levels.

5.1. Limitations

The limitation of the study is that study is restricted to the G7 nations. A similar analysis can be replicated in other economies for comparative analysis. For future purposes, the inclusion of other novel and innovative variables that directly or indirectly impact energy-related emissions can be investigated.

Authors statement

Li Zheng: Original Idea; Paper Writeup.
Ling Yuan: Paper Review; Revision.
Zeeshan Khan: Analysis and Methodology.
Ramez Abubakr Badeeb: Overall paper review; draft improvement; grammatical mistakes corrections.
Leilei Zhang: Supervision; Overall paper review; Technical Support.

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Appendix A. Supplementary data

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