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GREEN SUPPLY CHAIN AND INDUSTRY 4.0 DRIVEN CARBON NEUTRALITY PRACTICES IN TECHNOLOGICALLY ADVANCED COUNTRIES: A CIRCULAR ECONOMY PERSPECTIVE

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Annotation. Global warming is a persistent challenge which needs wide-ranging solutions. Excessive reliance on non-renewable resources and industrialization has caused an increase in waste generation which calls for worthy strategies to reduce CO_2 emissions by 2030 and meet zero carbon goal by 2050. Therefore, observing the relationship between green practices and circular economy is critical to address the carbon neutrality target. The present study scrutinizes how green logistics and artificial intelligence shape circular economy by considering factors such as economic growth, R&D, green taxes and renewable energy. The center focus of the study is technologically advanced economies covering the period from 2000 to 2023. The study employed Method of Moments Quantile Regression (MMQR) approach and reveals the artificial intelligence facilitates green logistics however, green logistics have no significance over circular practices in the given sample. Similarly, renewable resources and R&D have no direct impact on country's economic growth, however, country's growth and environmental taxes play major role in circular economy principles. To ensure robustness, the study also employed Feasible Generalized Least Square (FGLS) and validates the findings of MMQR. Given the scenario, the study encourages policy makers to show greater support to sustainable green logistic operations and AI- driven technologies in order to achieve carbon neutral goals.

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JEL classification: Q01; Q53; O33; O44.

Introduction

The progressive stage of industrialization with excessive reliance on non-renewable resources significantly increase global atmospheric pressure leading to various environmental challenges such as higher % of greenhouse emissions (Sadiq *et al.*, 2024). The average CO2 concentration has been increased from 285 to 419 (ppm) from pre-industrial era to year 2022. In addition, the temperature as well as the average CO2 concentration will continue to rise in the absence of efficient policies to limit or regulate CO2 emissions (Zhang *et al.*, 2025; Chen *et al.*, 2022). Therefore, in this persistent need to address the issue of global climate change and GHG emissions, countries have legally committed to achieve carbon neutrality (CN) through the creation of national laws, the signing of accords, the declaration of policies and different verbal commitments (Wu *et al.*, 2022). Many companies, governments and organizations are determined to achieve CN to reduce environmental degradation and enhance sustainability as it is essential to create a sustainable future that protects the environment for future generations (Shen, 2023). Generally, the reduction of carbon emissions depend not only on one path, but rather it requires combined effect of several strategies aimed at reducing carbon emissions. Additionally, it entails taking action to eliminate carbon from the atmosphere using techniques including soil CO2 sequestration, carbon capture and storage, and reforestation. Several other measures such as technological innovations, policy guarantee mixture, multi-objective collaborations and financial support can lead to achieve CN objectives (Wu *et al.*, 2022).

Likewise, circular economy (CE) is of significant importance for achieving CN. The basic idea of CE was initially proposed by David Pearce and Kerry Turner who defined CE" as an industrial system which is regenerative or restorative by design and intention." However, the "end-of-life" concept is replaced by restoration as it refers to transform the use of energy towards more renewable energy, thus, eliminating the consumption of toxic chemicals, waste recycling and management through superior business models and products, material and system designs (Dat *et al.*, 2025). CE is made up of a number of closed-loop systems designed to reduce negative environmental effects and promote sustainable economic growth (Wilson *et al.*, 2022). In other words, CE is another way to attain CN by reducing resource inputs which generate more socio-economic value because on the one hand, CE changes the way the products are produced and consumed through resource conservation (Streimikis, *et al.*, 2024), which can efficiently increase resource output and carbon productivity and reduce carbon emitted from the supply chain, industrial chain and value chain, while on the other hand, by promoting the efficient recycling of waste and the circulation of production elements (WEI *et al.* , 2021).

Therefore, it is important to analyze the wider implications of CE in this pressing need of CN. However, the applications of the CE concept into practice calls for advanced instruments and technologies that can effectively manage waste, improve resource consumption, and build closed-loop structures. In this regard, the relevance of innovative technologies, particularly industry 4.0 technologies such as artificial intelligence (AI) in promoting sustainable CE cannot be ignored (Rehman *et al.*, 2025). AI has significant role in transforming the economies from linear to CE by providing potent data driven solutions to several challenges related to waste reduction, resource management, and transparency in supply chain management (Gandia *et al*.,2025). AI-powered platforms facilitate the renting, redistribution and sharing of goods and promote a shift of linear consumption models to more sustainable consumption patterns. Additionally, AI plays significant role in making manufacturing sustainable through 3D printing, eco-design, projecting maintenance, reducing material waste and extending product lifecycles (Bashynska, Prokopenko, 2024). Furthermore, AI may play a crucial role in facilitating systemic change (Noman *et al*., 2022). AI also promote resource efficiency by identifying different opportunities for optimizing the resource consumption patterns (Singh, 2023). This makes the role of AI in attaining sustainable CE highly relevant to future and current CN agenda.

Likewise, supply chain performances can impact CE performances. Implementation of CE practices demands a total shift of production process to produce goods using green production and supply chain practices. In fact, green supply chain (GSC) minimizes material flow and negative environmental effects of consumption and production processes by integrating environmental issues into organization's production processes (Ying, Li-jun, 2012). Several GSC practices such as green logistics (GL) is one of the new business strategies that must be implemented in order to transition from linear to CE business models (Cheng *et al*., 2023). The focus of GL is on CE practices such as waste management, material handling and sustainable transportation, all of which reduces the energy and environmental footprints of the products' distribution. GL components including green transportation, packaging, distribution, warehousing etc. significantly reduce the material consumption, and promote the recycling and reuse of waste material. To create more value for customers and satisfy their needs, GL activities are linked to the environmentally responsible management of the movement of information and goods. Different GL activities including the use of green packaging, green shipping, green storage, and green processing processes help to achieve CE (Cheng *et al*., 2023). In essence, green logistics not only measure environmental consequences but also minimize waste generation and energy usage across logistics operation (Seroka-Stolka, Ociepa-Kubicka, 2019).

Amid these circumstances, the present study aims to analyze the role of GSC and AI in promoting CE in the context of the global technologically advanced economies namely China, Finland, Germany, Sweden, Switzerland, UK, USA, Japan, Singapore, South Korea over 2000 to 2023 period. Since these countries have seen rapid advancement in technology over the period of time, it is important to understand how technological progress have impacted CN target of these countries. At the same time, these countries are not performing well in terms of limiting their annual CO2 emissions and their increasing emission levels have continuously worsened their environmental quality. China, Germany, UK, the USA, South Korea, Japan are among the highest carbon emitting countries (Khan *et al*., 2025; Jun *et al*., 2022; Mohmmed *et al*., 2019) and these countries plan to reduce GHG emissions over next decade (Shpak *et al*., 2022). Besides, as evident from *Figure 1*, CO2 emissions in selected countries have progressively increased over 2000 to 2022 period. Therefore, it is not unexpected that these countries have completely failed to reduce their CO2 emissions and attaining CN targets. However in year 2020, some of the major economies such as Canada and Germany announced to reach CN target by 2050. China, being one of the major contributors to CO2 emissions, made commitment to achieve CN by 2060. Switzerland has made commitment to reduce its GHG emissions level by 2030 and Sweden has set this target to be achieved by 2050 (Li *et al*., 2020; Sandberg, Krook-Riekkola, 2022; Wu *et al*., 2022).This provides rationale for evaluating the role of latest and advanced technologies and GSC in achieving CN targets by promoting CE practices in the selected countries.

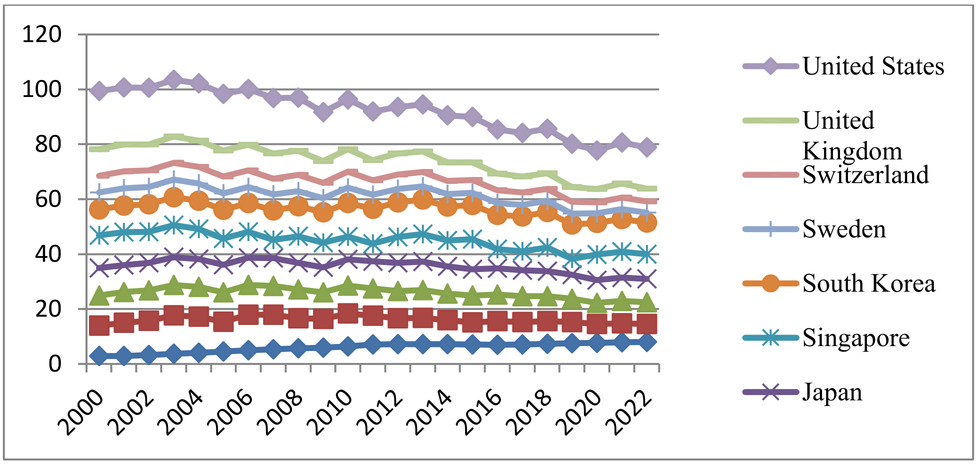

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Figure 1. **Trend of CO_2 Emissions in Technologically Advanced Countries, 2000-2022**

The study significantly contributes to the literature by bridging following literature gaps: First of all, there has been scarcity of empirical studies investigating the role of GSC and industry 4.0 in achieving CN in the context of the global technologically advanced economies using CE as indicator of CN. Second, although several studies have provided insights into how GSC and industry 4.0 has determined CE at firm level, not much empirical evidence is available regarding their role in CE at macro level. Also, earlier studies have not used the panel comprising of these technologically advanced economies to analyze the influence of the selected determinants on CE practices. Third, the existing studies have mostly investigated the impact of industry 4.0 technologies and GSC on CE using linear estimation approaches. However, it is imperative to analyze their impact using non-linear estimation approaches to determine whether their impact varies across various quantiles or cross sections. Accordingly, the present study bridges this gap by using MMQR estimation approach for assessing the relationship between selected regressors and CE which provides efficient estimation in the presence of cross sectional dependence (CSD), data non-normality and non-linear relationship between constructs (Liao *et al*., 2024).

The remaining portion of the study is categorized in to further sections. Literature review offers the detail preview of literature to identify the literature gap. The methodology section covers data and technique part which is followed by data analysis. The last section of the study concludes the findings by offering some implications and future directions.

1. Literature Review

1.1 Industry 4.0 and Circular Economy

Several recent studies have advocated for industry 4.0 technologies adoption to promote CE practices (Sadiq *et al*., 2025; Chien *et al*., 2025). Research studies suggest that advanced technologies such as “big data analysis, the Internet of Things, block-chain, cloud computing, AI and additive manufacturing” can facilitate the implementation of CE practices. These technologies help in transition from linear to CE by promoting the development of circular business models (Jugend *et al*., 2024). In this regard, Bag *et al*. (2021) explored the role of industry 4.0 in CE in manufacturing firms and revealed that industry 4.0 has positive impact on CE by having positive impact on sustainable production. Lei *et al*. (2023) also revealed that integration of different technologies had positive impact on CE. Study of Rizvi *et al*. (2023) indicated that CE and industry 4.0 nexus promoted asset analysis, waste reduction and post consumption product management. de Sousa Jabbour *et al*. (2022) studied the individual as well as joint impact of CE and Industry 4.0 on manufacturing firms' performance in Brazilian context. According to the findings, joint adoption of Industry 4.0 and CE had synergic effects on firm's performance in Brazil. Ghoreishi & Happonen (2020) explored the role of AI in CE at product design phase and disclosed that implementation of AI promoted CE in manufacturing process.

In continuation, Lanzalonga *et al*. (2024) studied the role of AI in decision making for promoting CE practices in an Italian multinational firm. The primary data collected was analyzed by Gioia method. The findings illustrated that AI played proactive role in promoting waste management transformation process. Jugend *et al*. (2024) analyzed the data of 248 companies in Brazil and confirmed that technologies have positive impact on CE and their combined effect enhanced firm performance. Likewise, taking data of the small and medium enterprises (SMEs) of the European countries, Findik *et al*. (2023) also concluded that industry 4.0 technologies enhanced or promoted the CE practices in SMEs.

1.2 Green Supply Chain and Circular Economy

Some earlier studies have studied empirical and theoretical relationship between GSC and CE, but the relationship between them is uncertain and received less empirical attention. Du *et al*. (2023) evaluated GL in carbon neutrality in BRICS-T countries over 2000 to 2018 period and confirmed the positive role of GL in promoting CN. Taking data of 212 small and medium enterprises, Centobelli *et al*. (2021) studied the role of GSC on CE and showed that GSC impacted CE positively. Likewise, Abdallah *et al*. (2024) studied the role of GSC management under the mediating role of green innovations in CE in 278 manufacturing firms of Jordan. The results of the study indicated that GSC management was positively related with CE and green innovations positively mediated the CE and GSC management relationship. Taking data of 211 garment manufacturing firms in Bangladesh, Cheng *et al*. (2023) indicated that green logistics promoted CE in garment manufacturing firms. Likewise Jinru *et al*. (2022) assessed the role of GL in CE in Chinese firms in 2020 and indicated that GL had positive impact on CE. Considering the data of energy related enterprises in Saudi Arabia, Nassani *et al*. (2023) analyzed the mediating role of GSC in green technologies and CE relationship. The analysis revealed that GSC positively mediated the green technologies and CE relationship.

In continuation, Sharma, Luthra, Joshi, Kumar, and Jain (2023) studied the role of GL and industry 4.0 technologies in CE adoption by industries in North India. PLS-SEM estimation was used and the outcomes revealed that industry 4.0 positively impacted CE and this relationship was positively mediated by GL. Taking the data of ASEAN economies, Torasa and Mekhum (2020) analyzed the role of GL in CE for 2000 to 2015 period. According to the estimates of the Fixed Effects, Random Effects and OLS approaches, GL had significant impact on CE. Zahran (2024) analyzed the impact of GSC on CE by considering data of 50 manufacturing firms. The outcomes of the study confirmed that GSC enhanced CE practices.

1.3 Gaps in the Extant Literature

The review of literature reveals some significant gaps which present study aims to address and fill. First of all, it is clear that many research studies have been conducted at micro and firm level and, to our knowledge, not many studies have been conducted using macro data for analyzing the relationship between GSC, Industry 4.0 and CE. Second, to our best knowledge, no prior study had attempted to evaluate the role of GSC and industry 4.0 in CE using panel data of technologically advanced countries. Therefore, the present study aims to fill these existing literature gaps.

2. Data and Method

2.1 Data

The present study uses annual data of top ten technologically advanced countries namely China, Finland, Germany, Sweden, Switzerland, UK, USA, Japan, Singapore, South Korea over 2000 to 2023 period retrieved from two main data sources namely "Organization for economic cooperation and development (OECD) and the World Development Indicators (WDI)."

Table 1. Variables of the Study and their Measurements

Variables	Measurement	Data Source
Circular Economy	Resource productivity measured as the ratio between domestic material consumption (million tons) and total GDP	Author's calculation
Green logistics	CO_2 intensity from logistics measured as the ratio between CO_2 emissions from transport sector and total GDP	Author's calculation
Artificial intelligence	Patents in technologies related to artificial intelligence	OECD
Economic growth	GDP per capita constant (US$ 2015)	WDI
Environmental taxes	Environment related taxes (% of GDP)	OECD
Renewable energy	Renewable energy consumption (% of total energy consumption)	WDI
Research and development	Research and development expenditures (% of GDP)	WDI

Source: created by the authors.

The dependent variable of the study is CE measured by resource productivity which is calculated by GDP ratio to domestic material consumption proposed by (Robaina, Villar, Pereira, 2020). This ratio indicates GDP produced per unit of resources used in a country. Two main explanatory variables considered by the present study are GSC and AI. GSC is measured by green logistics measured by CO2 intensity from logistics proposed by Ouni and Ben Abdallah (2024). GL is measured as the ratio between CO2 emissions from the transport sector and total GDP. AI is measured by patents in technologies related to artificial intelligence. Among the control variables, the study uses economic growth measured in terms of GDP per capita constant (US$, 2015), renewable energy consumption (measured by percentage of renewable energy consumption in total energy consumption), environment related taxes (ERT) (measured as % of GDP) and research and development (measured by research and development expenditures as percentage of GDP). The data for CE, ERT and AI is collected from OECD database and data for GL, economic growth, renewable energy and research and development is taken from WDI database.

2.2 Model Specification

Keeping in view the core objective, the baseline model of the study is specified on the basis of the Ecological Modernization Theory (EMT) proposed by Hajer (1997). EMT theory hypothesizes that environmental problems caused by economic growth can be decreased by raising resource productivity, resource efficiency as well as improving sustainability using technological developments and GSC practices which enhance environmental and economic performances simultaneously (Alahmad, El-Sadat, Ahmed, 2023). Therefore, EMT can provide us the theoretical background for analyzing the relationship between AI, GSC and CE as CE refers to an economic system which emphasizes the renewable energy consumption, material recovery and recycling and therefore it minimizes the negative environmental effects of the production system (Marrucci, Daddi, Iraldo, 2021). The literature also highlights the potential of CE for reducing inputs and recycling of waste materials to gain better quality of life by enhanced resource efficiency (Lanzalonga *et al*., 2024). Under the EMT framework, technological advancements such as AI can facilitate CE practices as AI has a significant role to play in remote and automatic monitoring of the efficiency of manufacturing processes as well as the product lifecycles. Moreover, AI efficiently handles the data generated during manufacturing, usage of products and disposal, all of which lead to promote CE practices (Özsoy, 2023). Likewise, GSC may also aid in improving operational and environmental performances through decline in resource and energy consumption, improving the efficiency in process and product design which help reduce waste generation through better cooperation and coordination between customers and suppliers (Q. Zhu, Sarkis, Lai, 2012). Therefore, under the framework of EMT theory, the baseline model of the study is formulated as:

$$CE = f\,(AI, GSC) \tag{1}$$

And the econometric form of the model is written as:

$$CE_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 GSC_{it} + \mu_{it} \tag{2}$$

Moreover, taking the support from Upadhayay, Shamsa, Khashadourian, and Sherm (2023), Robaina *et al*. (2020), and (Upadhayay *et al*., 2023), we add economic growth, research and development, environmental taxes and renewable energy as control variables in the study and elaborated the model as follows:

$$CE_{it} = \beta_0 + \beta_1 AI_{it} + \beta_2 GSC_{it} + \beta_3 RE_{it} + \beta_4 RD_{it} + \beta_5 EG_{it} + \beta_6 ERT_{it} + \varepsilon_{it} \tag{3}$$

Where, β's are the parameters to estimate, subscripts i and t denote cross sections (1,2,3,....,10) and time period (2000 to 2023). CE, AI, GSC, RE, RD, ERT and EG represent circular economy, artificial intelligence, renewable energy consumption, research and development, environmental taxes and economic growth, respectively.

2.3 Method of Analysis

2.3.1. Cross Sectional Dependence and Slope Heterogeneity Tests

In order to analyze panel data, it is of utmost importance to check cross sectional dependence (CSD) and slope heterogeneity problems. The CSD issue arises mainly due to local and global common economic shocks, financial or economic integration, globalization, unobserved components and oil price shocks (Hanif, Nawaz, 2024; Sun, Meng, Nawaz, Hanif, 2024). These issues can lead to biased and inefficient results if not dealt properly (Hanif, Nawaz, Hussain, & Bhatti, 2022). The CSD test equation proposed by Pesaran (2004) can be written as:

$$CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right) \sim N(0,1)i,j \tag{4}$$

The pair-wise correlation coefficient is shown by $\hat{\rho}_{ij}$ in equation (4). Similarly, we examine slope heterogeneity issue using (Pesaran, Yamagata, 2008) test. Differences in economic and demographic structures lead to slope heterogeneity issue. The basis equations of slope heterogeneity test are provided as follows:

$$\tilde{\Delta} = \sqrt{N}\,\left(\frac{N^{-1}\tilde{S}-k}{\sqrt{2k}}\right) \tag{5}$$

$$\tilde{\Delta}_{adj}=\frac{\sqrt{N}[N^{-1}\tilde{S}-E(\tilde{Z}_{it})]}{\sqrt{Var(\tilde{Z}_{it})}} \quad (6)$$

Where, $\tilde{\Delta}$ and $\tilde{\Delta}_{adj}$ represent delta tilde and adjusted delta tilde, respectively.

2.3.2 Panel Unit Root Test

Unit root or stationarity analysis is necessary to assess the order of integration among variables. Since the first generation tests are not robust to CSD and slope heterogeneity issues, therefore, the second-generation panel unit root tests are conducted in the present study. In this regard, the ‘cross sectional IPS” (CIPS) and “cross-section augmented Dickey-Fuller” (CADF) unit root tests proposed by Pesaran (2007) are used in the present study. The CADF unit root test uses cross-sectional mean of the lagged and first difference for each observation (Nawaz, Ahmad, Hussain, & Bhatti, 2020). The CADF test can be written in equation form as:

$$\Delta y_{it} = \alpha_i + \rho_i^* y_{it-1} + d_0 \bar{y}_{t-1} + \sum_{j=0}^{p} d_{j+1} \overline{\Delta y}_{t-j} + \sum_{k=1}^{p} c_k \Delta y_{it-k} + \varepsilon_{it} \quad (7)$$

where, Δy_{it} denotes the cross-sectional mean. Further, CIPS test statistics can be obtained by using CADF statistics as follows:

$$\text{CIPS}=\frac{1}{N}\sum_{i=1}^{N} CADF_i \quad (8)$$

2.3.3 Method of Moment Quantile Regression (MMQR)

The study has used MMQR estimation approach proposed by Machado and Silva (2019) to analyze the relationship between dependent and independent variables across different quantiles which is a fixed effect approach. As compared to traditional quantile regression techniques, MMQR is capable of taking into account the unobserved heterogeneity in panel data, allowing individual effects to impact the entire distribution (Zheng, Mousa, Mat Nawi, Nawaz, Hanif, 2024). This enables us to observe the conditional heterogeneous covariance effects of the independent variables. As a renowned non-linear estimation, MMQR also takes into account the location-based asymmetry of the dependent variable, as the location of the dependent variable determines the estimated parameters. Moreover, instead of just moving averages, the MMQR approach enables individual effects to impact the whole distribution and is highly effective to apply when data contains endogenous variables (Sun *et al*., 2024). The basic equation of MMQR is given in equation (8), which is used to assess the conditional quantile Qy(|X) as below:

$$Y_{it} = \dot{\alpha}_i + X_{it}\emptyset + (\lambda_i + Z'_{it}\psi)\ddot{U}_{it} \quad (8)$$

Where, (λi + Ƶ ʹ it ψ > 0) equal to 1 represents probability and (λi, α̇i) denote the fixed effects. Ƶ shows the k vector modules of Ẍ. The variation in equation (8) is shown in equation (9) as follows:

$$Z_j = Z_j(\ddot{X}).j = 1 - k \quad (9)$$

Where, $\ddot{U}_{it}$ and $\ddot{X}'_{it}$ are identically distributed. $\ddot{U}_{it}$ represents moment conditions which are orthogonal to $\ddot{X}'_{it}$ series. We can alternatively write equation (9) as:

$$Q_y\ (\delta !\ \ddot{X}'\text{it}) = (\lambda_i q(\delta) + \dot{\alpha}_i) + Z'_{it} + \ddot{X}_{it}\ \rho\ \bar{\varrho}\ q(\delta) \quad (10)$$

In above equation, the vector of all determinants is represented by Ẍ i.e., CE,GSC, AI, EG, RE and RD. Qy (d| $\ddot{X}'_{it}$) shows the quantile distribution of the dependent variable $\dot{Y}_{it}$ and dependent variable constrains the location of the independent variables. α̇i (**δ**)≡ ƛi q (**δ**) + α̇i represents a scalar showing fixed effects (**δʹ**) in quantiles. The following optimization is solved to achieve the individual quantiles which are represented by q(**δ**).

$$Min_q = \sum_i \sum t\eta\delta\, q(R_{it} - (\lambda_i + Z'_{it}\gamma)) \tag{11}$$

And ήO (Ȑ) = TȐÎ (Ȑ > 0) + (**δ** − 1) ȐÎ and (Ȑ < 0) represents the calculated operator.

2.3.4 Feasible Generalized Least Square (FGLS) Approach as Robustness Check

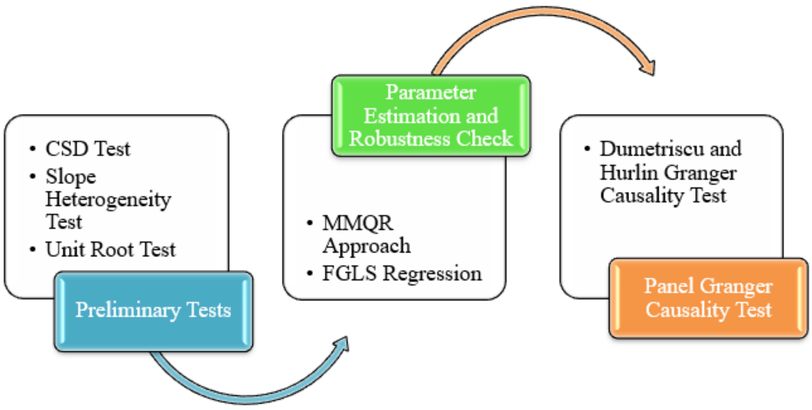
As a robustness check, we employed the FGLS estimation approach proposed by Parks (1967). In the presence of CSD issue, FGLS estimator is efficient than the OLS estimator. FGLS is suitable linear regression estimator in the presence of cross sectional correlation, serial correlation and heteroskedasticity. FGLS regression approach is more efficient and consistent than OLS approach. FGLS provides consistent, valid and efficient estimation when the time period component (T) is greater than the cross-section (N) (Nuţă *et al*., 2024). However, because it presumes that error terms are known, the FGLS estimator has been criticized for underestimating standard errors (Abbas, Yang, & Lahr, 2024).

2.3.5 Dumitrescu and Hurlin (2012) Granger Causality Test

The above mentioned parameter estimators do not indicate the causal association among the study variables. Therefore, to assess the direction of the causality among the variables, we apply the Dumitrescu and Hurlin's (2012) “granger causality” test. The main advantage of this approach is its ability to analyze imbalanced panel data and its efficient and robust estimation in the presence of the CSD and slope heterogeneity problems (Iqbal, Tang, & Rasool, 2023). The equation for this causality test is given as:

$$y_{it} = \alpha_0 + \sum_{j-1}^{k} \mu_i^j y_{i(t-j)} + \sum_{j-1}^{k} \gamma_i^j x_{i(t-j)} + \varepsilon_{it} \tag{12}$$

Where, x and y represent observables. The autoregressive parameters and regression coefficients are represented by μ_i^j and γ_i^j, respectively. The null hypothesis of the test assumes that there is no causal association and the alternative hypothesis assumes that causal association exists among the variables.



Source: created by the authors.

Figure 2. **Structural Diagram of Supply Chain Emission Reduction Activities**

The scheme of applied estimations is graphically shown in *Figure 2*.

3. Results and Discussion

First of all, the study performs some preliminary tests before proceeding to formal empirical estimation. In this regard, the descriptive statistics are given in *Table 2* which reports the detailed description about all data series including their mean, standard deviation, minimum and maximum values. The average value of CE is 2580900 with standard deviation of 1810900. The minimum value of CE is observed for China in 2000 and maximum value is observed for Switzerland in 2022. Similarly, mean or average value of AI is 335.35 with value of standard deviation 818.86. Among all selected countries, Switzerland has the minimum value (0.40) in 2004 and China has the highest value (5594.4) in 2023. Next, the values of mean and standard deviation of GL are 0.000542 and 0.000242, respectively. The data range of GSC lies between 0.000154 and 0.000125 and minimum value is possessed by Singapore in 2022 and USA has the maximum value in 2000. The mean and standard deviation value of RE are 15.219 and 15.122, respectively. The minimum value of RE is observed for Singapore in 2000 and Sweden has the maximum value in 2021. RD holds mean value of 2.713 and standard deviation of 0.737. China has the minimum value of RD in 2000 and South Korea has the maximum value in 2021. EG holds minimum value in 2000 in China and maximum value in Switzerland in 2022. The mean and standard deviation of EG are 42956.51 and 19247.49, respectively. Last, the value of mean and standard deviation of ERT are 100.2917 and 66.522, respectively. The minimum value of ERT is observed in the USA in 2023 and maximum value is found for Germany in 2021.

Table 2. Results of Descriptive Statistics Analysis

Variables	Mean	Standard Deviation	Minimum Value	Maximum Value	Jarque-Bera Statistics
CE	2580900	1810900	2260800	8990900	123.6***
AI	335.35	818.86	0.400	5594.4	3034.1***
GSC	0.000542	0.000242	0.000154	0.000125	25.594***
RE	15.219	15.122	0.3000	57.900	43.378***
RD	2.713	0.737	0.893	4.930	0.067
EG	42956.51	19247.49	2193.897	90057.04	2.141***
ERT	100.2917	66.52283	-23	216	14.8***

Note: *** denotes significance at 1%.

Source: created by the authors.

Table 3. Correlation Matrix

Variables	CE	AI	GSC	EG	RE	RD	ERT
CE	1.000						
AI	-0.006**	1.000					
GSC	-0.535	0.277	1.000				
EG	0.0805	-0.140	-0.595	1.000			
RE	-0.088*	-0.228	-0.208	0.206	1.000		
RD	0.280	0.302	-0.017**	0.235	0.292	1.000	
ERT	0.122	-0.317	0.036**	-0.019**	0.408	0.166	1.000

Note: *&** represent 10% and 5% significance level.

Source: created by the authors.

Correlation matrix indicating the strength and direction of the association among concerned variables is given in *Table 3*. The matrix indicates that only AI and RE are significantly correlated with CE and all other variables have no significant correlation with CE. Moreover, the value of correlation is less than 0.8 which shows that multicollinearity problem does not exist in specified model.

Table 4 shows the results of the CSD analysis conducted to assess the absence or presence of the CSD issue. The Pesaran (2004) test statistics are significant at 1% for all variables indicating that the issue of CSD is present in our data.

Table 4. Results of CSD Test

Variables	Test statistics	P-value
CE	18.354***	0.000
AI	31.119***	0.000
GSC	30.288***	0.000
RE	13.162***	0.000
RD	15.629***	0.000
EG	31.402***	0.000
ERT	8.853***	0.000

Note: *&** represent 10% and 5% significance level.

Source: created by the authors.

Likewise, the test statistics for slope heterogeneity test are given in *Table 5*. The highly significant test statistics strongly reject the null hypothesis of slope homogeneity revealing that slope heterogeneity exists in our data.

Table 5. Results of Slope Heterogeneity Test

Dependent variable=CE	Test stat	P-value
Delta tilde	7.680***	0.000
Adjusted delta tilde	9.416***	0.000

Note: *** denotes significance at 1%.

Source: created by the authors.

Table 6 presents the results of the "cross-sectional augmented IPS" (CIPS) and "cross-sectional augmented Dickey Fuller" (CADF) panel unit root tests proposed by (Pesaran, 2007). On the basis of the findings, we are able to conclude that panel data series have mixed order of integration as some of the series are stationary at first difference and some data series are stationary at level.

Table 6. Results of Unit Root Tests

Variables	CIPS	CADF		
	Level	First Difference	Level	First Difference
CE	-1.992	-4.435***	-1.739	-3.246***
AI	-3.276***	---------	-1.879	-3.104***
GL	-1.703	-4.204***	-2.046	-3.194***
RE	-1.252	-4.184***	-0.990	-4.184***
RD	-2.542**	---------	-2.059	-2.896***
EG	-1.462	-3.217***	-2.001	-2.824***
ERT	-0.904	-3.609***	-0.955	-2.333***

Note: *** & ** denote significance at 1% and 5%.

Source: created by the authors.

This study employed MMQR method for parameter estimation and the outcomes indicating the relationship between dependent and independent variables are given in *Table 7*. According to the outcomes, AI has a significant positive impact on CE with decreasing magnitude from lower to higher quantiles. For each unit increase in AI, CE increases by 0.031 to 0.070 units from 1st to 9th quantiles. This finding implies the relevance of AI in promoting sustainable CE in technologically advanced countries. AI has the potential to facilitate all central principles of CE such as it optimizes resource consumption, enhances waste management, and aid in efficiently manage the product lifecycle (Bashynska, Prokopenko, 2024). The outcome is consistent with Onyeaka *et al*. (2023) who argued that AI possesses the potential to find out the opportunities for the management and recycling of the waste materials which are important determinant of CE. Likewise, the findings are consistent with Roberts *et al*. (2024) who claimed that AI help in designing sustainable robust products and aid in new business models.

Table 7. Results of MMQR Estimation

Series	Location	Scale	Quantiles								
			0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90
AI	0.052***	0.0123*	0.0310	0.037**	0.043**	0.047**	0.0525***	0.059***	0.0627***	0.0658***	0.070***
	(0.000)	(0.090)	(0.149)	(0.049)	(0.004)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GSC	-0.383**	-0.169***	-0.089	-0.172**	-0.257***	-0.310***	-0.385***	-0.479***	-0.525***	-0.525***	-0.627***
	(0.000)	(0.000)	(0.249)	(0.013)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
EG	0.0000***	-0.0003***	0.00003***	0.00003***	0.00003***	0.00003***	0.00003***	0.00003***	0.00002***	0.00002***	0.00002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
RE	-0.0226***	0.0014	-0.025***	-0.0244***	-0.0236***	-0.023***	-0.0225***	-0.0217***	-0.0214***	-0.0210***	-0.020****
	(0.000)	(0.150)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
RD	0.139***	0.0015	0.137**	0.137**	0.138***	0.139***	0.1397***	0.1405***	0.140***	0.141***	0.141***
	(0.000)	(0.929)	(0.007)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ERT	0.0041***	0.0005**	0.0032***	0.0035***	0.0037***	0.0039***	0.0041***	0.0044***	0.0045***	0.0047***	0.0049***
	(0.000)	(0.014)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note: ***, ** and * denote significance at 1, 5 and 10 percent and p-values are given in parentheses.

Source: created by the authors.

The other important finding shows that GSC measured by GL is significantly and negatively related to CE. A one unit increase in GL leads to 0.089 to 0.624 units decrease in CE from 1st to 9th quantiles. This outcome implies that GL activities are not conducive to promote CE practices in concerned economies. A possible justification of this unexpected and contradictory finding can be the interdependencies of different GSC activities and therefore the efforts in one area compromise the sustainability in other areas. For example, reusable packaging systems reduce costs and enhance resource efficiency but also increase the number of logistics routes which increase the energy use and transport related emissions which create hindrance to adopt CE practices (Zhou, Siddik, Zheng, Masukujjaman, 2023). The outcomes of the study are in-line with Torasa and Mekhum (2020) as they found that GL are negatively related to recycling of waste material. However, the findings are not in line with Jinru *et al*. (2022) as the authors claimed the positive impact of GL on CE in manufacturing firms in China. The findings are also in contradiction with the findings of Torasa and Mekhum (2020) as the authors found that logistic operations help promote recycling rate in ASEAN countries.

In contrast, RD indicates positive association with CE. For one percent increase in RD, CE increases by 0.137 to 0.141 units from 1st to 9th quantile. This expected relationship between RD and CE is supported by the findings of Hammar and Belarbi (2021) who found that in some cases, RD affects CE positively. Likewise, the outcomes of Ildırar, Özmen, and İşcan (2016) favour our findings as they argued that RD expenditures play positive role in promoting resource productivity. However, the findings of Robaina *et al*. (2020) are not consistent with the outcomes of the present study and the authors argued that research and development investments might not be for made in areas which are necessary for improving productivity. As far as the impact of EG on CE is concerned, the estimates shows that increase in economic growth facilitate CE practices in technologically advanced countries. A one unit increase in EG is predicted to increase CE by 0.00003 to 0.00002 units from 1st to 9th quantiles, respectively. This finding is in line with Upadhayay *et al*. (2023) who conclude that increase in EG shows the expansion or growth of an economy which brings many opportunities to employ and practice circular economy strategies. Likewise, Aydınbaş and Erdinç (2023) also strongly favor our findings by concluding the favourable contribution of EG in CE in European countries.

Unexpectedly, it has been observed that RE fails to ensure CE in technologically advanced countries. The significant and negative coefficients denote that a one percent rise in RE reduces CE by 0.025 to 0.020 units from lowest to the highest quantile. The findings are contradictory to Robaina *et al*. (2020) who argued that RE has positive association with CE. Lastly, the coefficient of ERT is also statistically significant and positive across all quantiles. A one percent increase in ERT is found to increase CE by 0.0032 to 0.0049 units from 1^{st} to 9^{th} quantiles. This finding indicates that shifting of the tax burden from capital and labour helps improve competitiveness and productivity (Robaina *et al*., 2020). The finding is in-line with Siedschlag, Meneto, and Tong Koecklin (2022) as the authors find that environmental regulations increase green innovations use by firms which enhances CE practices. Likewise, Milios (2021) support our results by arguing that CE is a complex process which can be facilitated by proper policy interventions.

Table 8. FGLS Estimates for Robustness Check

	Coefficient	P-value
AI	0.052***	0.000
GL	-0.383***	0.000
RE	-0.022***	0.000
RD	0.139***	0.000
EG	0.00003***	0.000
ERT	0.0041***	0.000

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

Source: created by the authors.

Table 9. Results of Granger Causality Test

Null hypothesis	Z-bar statistics	Prob-value
GSC does not homogeneously cause CE	3.991***	0.000
CE does not homogeneously cause GSC	1.904**	0.050
AI does not homogeneously cause CE	2.294**	0.021
CE does not homogeneously cause AI	3.419***	0.000
EG does not homogeneously cause CE	2.333**	0.019
CE does not homogeneously cause EG	0.063	0.949
RE does not homogeneously cause CE	0.276	0.782
CE does not homogeneously cause RE	0.709	0.477
RD does not homogeneously cause CE	0.993	0.320
CE does not homogeneously cause RD	3.675***	0.000
ERT does not homogeneously cause CE	-0.671	0.501
CE does not homogeneously cause ERT	0.892	0.371

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

Source: created by the authors.

As a robustness check, we re-estimate the model using the FGLS estimator and corresponding results are reported in *Table 8*. The similarity of the significance and sign of the estimates from both methods establish the robustness of the findings across the regression techniques used in this study. Finally, the robustness check is followed by the granger causality testing.

Source: created by the authors.

Figure 3. **Granger Causality Analysis (Visual Representation)**

Table 9 reports the findings of panel causality analysis. We find that bidirectional causality is present between AI, RE, ERT and CE. RD is found to cause CE and CE is found to cause EG in unidirectional way. However, no causal link is found to be present between GSC and AI. Figure 3 provides visual representation of the granger causality analysis.

Conclusions and Policy Implications

Attainment of the target of carbon-neutral by 2050 requires undertaking efficient measures such as CE practices which are helpful in mitigating the CO2 emission levels. In this regard, the present study explored the relationship between GSC, AI and CE in the context of most technologically advanced countries over 2000 to 2023 period. Using advanced econometric techniques such as MMQR and FGLS, the study has indicated that AI facilitates but GSC does not promote CE practices in concerned countries. As far as the role of pertinent control variables is concerned, the findings have revealed that economic growth, environmental taxes promote, but research and development promote and renewable energy hinder the CE in concerned countries. Thus, the research highlights that the significance of AI and GSC practices regarding the implementation of CE initiatives to achieve CN target by 2050.

In order to reach this target as quickly as possible, the study suggests some worthy policies to maximize the contribution of AI to expedite the CE practices. First of all, governments must provide tax incentives and grants for research and development in AI-driven CE technologies and update regulations to facilitate AI-driven recycling and sorting technologies. More tax breaks should be offered to the business to implement CE practices like closed loop recycling using AI technologies. Likewise, government should subsidize AI driven practices for recycling, waste management and sorting. Second, as GL is observed to hinder CE practices, the governments should enact strict standards for managing end of life logistics and raw material sourcing to ensure compliance with CE principles. The government must provide tax breaks and subsidies for businesses which willingly adopt closed-loop supply chains and use recycled materials in logistics. Moreover, the research activities must be encouraged for promoting green logistics technologies including smart routing, energy efficient vehicles and low-impact packaging. These practices would help ensure that GL contribute significantly to CE objectives.

Besides the theoretical and empirical contribution to the literature, the limitations of the study are important to be acknowledged. The main limitation of the study is that it focused on top ten technologically advanced countries which can restricts the generalizability of its findings to other countries and regions having different environmental and economic conditions. For more generalized understanding of the role of GSC and AI in CE, future research studies must broaden up the scope by adding more countries from different geographical regions. Second, to have understanding of their role in CE, future research studies can be conducted at local level using macro level data of individual countries. Third, the study used AI and GL to measure industry 4.0 and GSC and ignore several other measures such as block-chain technologies, internet of things, cloud computing and green practices in manufacturing process which can be used by future research studies to provide more comprehensive role of these practices in CE. Furthermore, in order to compare the results, this study might also be carried out using different methodologies such as CS-ARDL, CCEMG, AMG, DCCEMG etc. as part of future research directions.

Literature

Abbas, M., Yang, L., Lahr, M.L. (2024), "Globalization's effects on South Asia's carbon emissions, 1996–2019: a multidimensional panel data perspective via FGLS", *Humanities and Social Sciences Communications*, Vol. 11, No 1, pp.1-19.

Abdallah, A.B., Al-Ghwayeen, W.S., Al-Amayreh, E.A.M., Sweis, R.J. (2024), "The Impact of Green Supply Chain Management on Circular Economy Performance: The Mediating Roles of Green Innovations", *Logistics*, Vol. 8, No 1, 20, https://doi.org/10.3390/logistics8010020.

Alahmad, Y.Y., El-Sadat, N.M., Ahmed, W.H.E.-G. (2023), "Examining the Influence Extent of I4 Technologies and Circular Economy Practices on Firm Organizational Effectiveness: Ecological Modernization Theory and Practice-Based View", *The Scientific Journal of Financial and Commercial Studies and Research*, Vol. 4, No 2, pp.827-861.

Aydınbaş, G., Erdinç, Z. (2023), "Panel Data Analysis on The Circular Economy And Its Determinants", *Anadolu Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*, Vol. 24, No 2, pp.258-275.

Bag, S., Yadav, G., Dhamija, P., Kataria, K.K. (2021), "Key resources for industry 4.0 adoption and its effect on sustainable production and circular economy: An empirical study", *Journal of Cleaner Production*, Vol. 281, January, 125233, https://doi.org/10.1016/j.jclepro.2020.125233.

Bashynska, I., Prokopenko, O. (2024), "Innovative Technologies and Digital Platforms: AI's Role in a Sustainable Circular Economy", *Scientific Journal of Bielsko-Biala School of Finance and Law*, Vol. 28, No 3.

Centobelli, P., Cerchione, R., Esposito, E., Passaro, R. (2021), "Determinants of the transition towards circular economy in SMEs: A sustainable supply chain management perspective", *International journal of production economics*, Vol. 242, December, 108297, https://doi.org/10.1016/j.ijpe.2021.108297.

Chen, L., Msigwa, G., Yang, M., Osman, A.I., Fawzy, S., Rooney, D.W., Yap, P.-S. (2022), "Strategies to achieve a carbon neutral society: a review", *Environmental Chemistry Letters*, Vol. 20, No 4, pp.2277-2310.

Cheng, Y., Masukujjaman, M., Sobhani, F.A., Hamayun, M., Alam, S.S. (2023), "Green logistics, green human capital, and circular economy: the mediating role of sustainable production", *Sustainability*, Vol. 15, No 2, 1045, https://doi.org/10.3390/su15021045.

Chien, F., Nisar, Q.A., Haider, S., Umrani, W.A., Zhang, Y., Leong, M.K. (2025), "Sustainable manufacturing in Chinese semiconductor enterprises: the mediating role of green circular economy and recycling and remanufacturing between Industry 4.0 and green HRM", *Journal of Enterprise Information Management*, pp.1-24.

Dat, P.T., Hang, N.P.T., Thuy, H.L.T. (2025), "Factors affecting the circular economy in Vietnam", *Contemporary Economics*, Vol. 19, No 2, pp.132-147.

de Sousa Jabbour, A.B.L., Jabbour, C.J.C., Choi, T.-M., Latan, H. (2022), "'Better together': evidence on the joint adoption of circular economy and industry 4.0 technologies", *International journal of production economics*, Vol. 252, October, 108581, https://doi.org/10.1016/j.ijpe.2022.108581.

Du, J., Cheng, J., Ali, K. (2023), "Modelling the green logistics and financial innovation on carbon neutrality goal, a fresh insight for BRICS-T", *Geological Journal*, Vol. 58, No 7, pp.2742-2756.

Dumitrescu, E.-I., Hurlin, C. (2012), "Testing for Granger non-causality in heterogeneous panels", *Economic modelling*, Vol. 29, No 4, pp.1450-1460.

Findik, D., Tirgil, A., Özbuğday, F.C. (2023), "Industry 4.0 as an enabler of circular economy practices: Evidence from European SMEs", *Journal of Cleaner Production*, Vol. 410, July, 137281, https://doi.org/10.1016/j.jclepro.2023.137281.

Gandia, J.A.G., de Lucas Ancillo, A., del Val Núñez, M.T. (2025), "The Role of Artificial Intelligence and Knowledge in Enhancing Corporate Sustainability", *Journal of Innovation & Knowledge*, Vol. 10, No 5, 100792, https://doi.org/10.1016/j.jik.2025.100792.

Ghoreishi, M., Happonen, A. (2020), "Key enablers for deploying artificial intelligence for circular economy embracing sustainable product design: Three case studies", *Paper presented at the AIP conference proceedings*.

Hajer, M.A. (1997), "The Historical Roots of Ecological Modernization", in: M.A. Hajer (ed.), *The Politics of Environmental Discourse: Ecological Modernization and the Policy Process*, Oxford University Press, pp.73-103, https://doi.org/10.1093/019829333X.003.0004.

Hammar, N., Belarbi, Y. (2021), "R&D, innovation and productivity relationships: Evidence from threshold panel model", *International Journal of Innovation Studies*, Vol. 5, No 3, pp.113-126.

Hanif, S., Nawaz, A., Hussain, A., Bhatti, M.A. (2022), "Linking non renewable energy, renewable energy, globalization and CO2 emission under EKC hypothesis: evidence from ASEAN-6 countries through advance panel estimation", *Pakistan Journal of Humanities and Social Sciences*, Vol. 10, No 1, pp.391-402.

Hanif, S., Nawaz, M.A. (2024), "Economic Complexity, Green Technologies and Environmental Degradation in World's Top Polluting Countries: Evidence from Advance Panel Estimation", *Pakistan Journal of Humanities and Social Sciences*, Vol. 12, No 3, pp.2605-2615.

Ildırar, M., Özmen, M., İşcan, E. (2016), "The effect of research and development expenditures on economic growth: new evidences", *Paper presented at the International Conference on Eurasian Economies*

Iqbal, A., Tang, X., Rasool, S.F. (2023), "Investigating the nexus between CO2 emissions, renewable energy consumption, FDI, exports and economic growth: evidence from BRICS countries. Environment", *Development and Sustainability*, Vol. 25, No 3, pp.2234-2263.

Jinru, L., Changbiao, Z., Ahmad, B., Irfan, M., Nazir, R. (2022), "How do green financing and green logistics affect the circular economy in the pandemic situation: key mediating role of sustainable production", *Economic research-Ekonomska istraživanja*, Vol. 35, No 1, pp.3836-3856.

Jugend, D., Fiorini, P.D.C., Fournier, P.-L., Latan, H., Jabbour, C.J.C., Scaliza, J.A.A. (2024), "Industry 4.0 technologies for the adoption of the circular economy: An analysis of institutional pressures and the effects on firm performance", *Journal of Environmental Management*, Vol. 370, November, 122260, https://doi.org/10.1016/j.jenvman.2024.122260.

Jun, W., Mughal, N., Kaur, P., Xing, Z., Jain, V. (2022), "Achieving green environment targets in the world's top 10 emitter countries: the role of green innovations and renewable electricity *production", Economic research-Ekonomska istraživanja*, Vol. 35, No 1, pp.5310-5335.

Khan, A., Salim, A.S., Pantamee, A.A., Tufail, B., Mirzaliev, S. (2025), "The Impact of Economic Outcomes on Sustainable Energy Technologies in The Top Ten Asian Countries", *Transformations in Business & Economics*, Vol. 24, No 1.

Lanzalonga, F., Marseglia, R., Irace, A., Biancone, P.P. (2024), "The application of artificial intelligence in waste management: understanding the potential of data-driven approaches for the circular economy paradigm", *Management Decision*.

Lei, Z., Cai, S., Cui, L., Wu, L., Liu, Y. (2023), "How do different Industry 4.0 technologies support certain Circular Economy practices?", *Industrial management & data systems*, Vol. 123, No 4, pp.1220-1251.

Li, X., Damartzis, T., Stadler, Z., Moret, S., Meier, B., Friedl, M., Maréchal, F. (2020), "Decarbonization in complex energy systems: a study on the feasibility of carbon neutrality for Switzerland in 2050", *Frontiers in Energy Research*, Vol. 8, 549615, https://doi.org/10.3389/fenrg.2020.549615.

Liao, X., Nawi, H.M., An, P.H., Mabrouk, F., Kholikova, R., Arnone, G., Sahawneh, N.M. (2024), "Influence of fintech, natural resources, and energy transition on environmental degradation of BRICS countries: Moderating role of human capital", *Resources Policy*, Vol. 92, May, 105022, https://doi.org/10.1016/j.resourpol.2024.105022.

Machado, J.A., Silva, J.S. (2019), "Quantiles via moments", *Journal of econometrics*, Vol. 213, No 1, pp.145-173.

Marrucci, L., Daddi, T., Iraldo, F. (2021), "The contribution of green human resource management to the circular economy and performance of environmental certified organisations", *Journal of Cleaner Production*, Vol. 319, October, 128859, https://doi.org/10.1016/j.jclepro.2021.128859.

Milios, L. (2021), "Towards a circular economy taxation framework: Expectations and challenges of implementation", *Circular Economy and Sustainability*, Vol. 1, No 2, pp.477-498.

Mohmmed, A., Li, Z., Arowolo, A.O., Su, H., Deng, X., Najmuddin, O., Zhang, Y. (2019), "Driving factors of CO2 emissions and nexus with economic growth, development and human health in the Top Ten emitting countries", *Resources, Conservation and Recycling*, Vol. 148, pp.157-169.

Nassani, A.A., Hussain, H., Condrea, E., Grigorescu, A., Yousaf, Z., Haffar, M. (2023), "Zero waste management: investigation of green technology, the green supply chain, and the moderating role of CSR intentions", *Sustainability*, Vol. 15, No 5, 4169, https://doi.org/10.3390/su15054169.

Nawaz, M.A., Ahmad, T.I., Hussain, M.S., Bhatti, M.A. (2020), "How energy use, financial development and economic growth affect carbon dioxide emissions in selected association of south east Asian nations?", *Paradigms(S1)*, pp.159-164.

Noman, A.A., Akter, U.H., Pranto, T.H., Haque, A. (2022), "Machine learning and artificial intelligence in circular economy: a bibliometric analysis and systematic literature review", *Annals of Emerging Technologies in Computing (AETiC)*, Vol. 6, No 2, pp.13-40.

Nuţă, F.M., Sharafat, A., Abban, O.J., Khan, I., Irfan, M., Nuţă, A.C., Asghar, M. (2024), "The relationship among urbanization, economic growth, renewable energy consumption, and environmental degradation: A comparative view of European and Asian emerging economies", *Gondwana Research*, Vol. 128, pp.325-339.

Onyeaka, H., Tamasiga, P., Nwauzoma, U.M., Miri, T., Juliet, U.C., Nwaiwu, O., Akinsemolu, A.A. (2023), "Using artificial intelligence to tackle food waste and enhance the circular economy: Maximising resource efficiency and Minimising environmental impact: A review", *Sustainability*, Vol. 15, No 13, 10482, https://doi.org/10.3390/su151310482.

Ouni, M., Ben Abdallah, K. (2024), "Environmental sustainability and green logistics: Evidence from BRICS and Gulf countries by cross-sectionally augmented autoregressive distributed lag (CS-ARDL) approach", *Sustainable Development*.

Özsoy, T. (2023), "The Role of Artificial Intelligence in Facilitating The Transition ta A Circular Economy", *Nişantaşı Üniversitesi Sosyal Bilimler Dergisi*, Vol. 11, No 2, pp.369-389.

Pesaran, M.H. (2004), "General diagnostic tests for cross section dependence in panels", *Cambridge Working Papers. Economics*, Vol. 1240, No 1, IZA.

Pesaran, M.H. (2007), "A simple panel unit root test in the presence of cross-section dependence", *Journal of applied econometrics*, Vol. 22, No 2, pp.265-312.

Pesaran, M.H., Yamagata, T. (2008), "Testing slope homogeneity in large panels", *Journal of econometrics*, Vol. 142, No 1, pp.50-93.

Rehman, A., Ma, H., Ahmad, M.I., Batool, Z., Tillaguango, B., Oláh, J. (2025), "The technology innovation paradox in Asia's leading innovative economies: the importance of renewable energy and green financing", *Technological and Economic Development of Economy*, pp.1-26.

Rizvi, S.W.H., Agrawal, S., Murtaza, Q. (2023), "Automotive industry and industry 4.0-Circular economy nexus through the consumers' and manufacturers' perspectives: A case study", *Renewable and Sustainable Energy Reviews*, Vol. 183, September, 113517, https://doi.org/10.1016/j.rser.2023.113517.

Robaina, M., Villar, J., Pereira, E.T. (2020), "The determinants for a circular economy in Europe", *Environmental Science and Pollution Research*, Vol. 27, No 11, pp.12566-12578.

Roberts, H., Zhang, J., Bariach, B., Cowls, J., Gilburt, B., Juneja, P., Floridi, L. (2024), "Artificial intelligence in support of the circular economy: ethical considerations and a path forward", *AI & SOCIETY*, Vol. 39, No 3, pp.1451-1464.

Sadiq, M., Nawaz, M.A., Sharif, A., Hanif, S. (2024), "Bridging green supply chain practices and environmental performance in Chinese semiconductor sector: With the role of energy efficiency and green HRM", *International journal of production economics*, Vol. 277, 109381, https://doi.org/10.1016/j.ijpe.2024.109381.

Sadiq, M., Mehmood, K., Leong, M.K., Ghani, U., Usman, M. (2025), "Industry 4.0 and Circular Economy: Examining the Role of Supply Chain Integration and Corporate Social Responsibility", *Corporate Social Responsibility and Environmental Management*, Vol. 32, No 6, pp.8242-8257.

Sandberg, E., Krook-Riekkola, A. (2022), "The impact of technology availability on the transition to net-zero industry in Sweden", *Journal of Cleaner Production*, Vol. 363, August, 132594, https://doi.org/10.1016/j.jclepro.2022.132594.

Seroka-Stolka, O., Ociepa-Kubicka, A. (2019), "Green logistics and circular economy", *Transportation Research Procedia*, Vol. 39, pp.471-479.

Sharma, M., Luthra, S., Joshi, S., Kumar, A., Jain, A. (2023), "Green logistics driven circular practices adoption in industry 4.0 Era: A moderating effect of institution pressure and supply chain flexibility", *Journal of Cleaner Production*, Vol. 383, January, 135284, https://doi.org/10.1016/j.jclepro.2022.135284.

Shen, R. (2023), "Utilizing Artificial Intelligence and Machine Learning to Facilitate Achieving Carbon Neutrality. Science and Technology of Engineering", *Chemistry and Environmental Protection*, Vol. 1, No 1.

Shpak, N., Ohinok, S., Kulyniak, I., Sroka, W., Fedun, Y., Ginevičius, R., Cygler, J. (2022), "CO2 emissions and macroeconomic indicators: Analysis of the most polluted regions in the world", *Energies*, Vol. 15, No 8, 2928, https://doi.org/10.3390/en15082928.

Siedschlag, I., Meneto, S., Tong Koecklin, M. (2022), "Enabling green innovations for the circular economy: what factors matter?", *Sustainability*, Vol. 14, No 19, 12314, https://doi.org/10.3390/su141912314.

Singh, J. (2023), "Artificial Intelligence in Circular Economies: A Pathway to Sustainable Resource Management", *International Journal of Science and Research (IJSR),* Vol. 12.

Streimikis, J., Ślusarczyk, B., Siksnelyte-Butkiene, I., Mura, L. (2024), "Development of circular economy in the Visegrad Group of countries", *Contemporary Economics*, Vol. 18, No 3, pp.365-375.

Sun, S., Meng, F., Nawaz, M.A., Hanif, S. (2024), "A re-assessment of the Resource Curse Hypothesis in top resource-rich developing countries: Fresh insights using method of moments quantile regression", *Natural Resources Forum*.

Torasa, C., Mekhum, W. (2020), "Impact of green logistics activities on circular economy: Panel data evidence from ASEAN", *International Journal of Supply Chain Management*, Vol. 9, No 1, pp. 239-245.

Upadhayay, S., Shamsa, K., Khashadourian, E., Sherm, A. (2023), "Determinants of Circular Economy: An Empirical Approach in the Context of the United States of America", *Journal of Applied Research*, Vol. 75.

Wei, W., Chen, Z., Geng, Y., Cai, W., Liu, H. (2021), "Toward carbon neutrality: Circular economy approach and policy implications", *Bulletin of Chinese Academy of Sciences (Chinese Version)*, Vol. 36, No 9, pp.1030-1038.

Wilson, M., Paschen, J., Pitt, L. (2022), "The circular economy meets artificial intelligence (AI): Understanding the opportunities of AI for reverse logistics", *Management of Environmental Quality: An International Journal*, Vol. 33, No 1, pp.9-25.

Wu, X., Tian, Z., Guo, J. (2022), "A review of the theoretical research and practical progress of carbon neutrality", *Sustainable Operations and Computers*, Vol. 3, pp.54-66.

Ying, J., Li-jun, Z. (2012), "Study on green supply chain management based on circular economy", *Physics Procedia*, Vol. 25, pp.1682-1688.

Zahran, S. (2024), "Investigating the Nexus between Green Supply Chain Practices and Sustainable Waste Management in Advancing Circular Economy", *Sustainability*, Vol. 16, No 9, 3566, https://doi.org/10.3390/su16093566.

Zheng, X., Mousa, S., Mat Nawi, H., Nawaz, M.A., Hanif, S. (2024), "Does resource richness help in uplifting the economic status of resource-abundant developing countries? Evidence from Organization of Petroleum Exporting Countries using methods of movements quantile regression". Natural Resources Forum.

Zhou, B., Siddik, A.B., Zheng, G.-W., Masukujjaman, M. (2023), "Unveiling the role of green logistics management in improving SMEs' sustainability performance: do circular economy practices and supply chain traceability matter?", *Systems*, Vol. 11, No 4, 198, https://doi.org/10.3390/systems11040198.

Zhu, Q., Sarkis, J., Lai, K.-h. (2012), "Green supply chain management innovation diffusion and its relationship to organizational improvement: An ecological modernization perspective", *Journal of Engineering and Technology Management*, Vol. 29, No 1, pp.168-185.

Zhang, L., Aldeehani, T.M., Riaz, S., Khan, A., Khudoykulov, K. (2025), "The Impact of Carbon Finance, Renewable Energy, and Environmental Knowledge on Load Capacity Factor", *Transformations in Business & Economics*, Vol. 24, No 3.

ŽALIOSIOS TIEKIMO GRANDINĖS IR PRAMONĖ 4.0 SKATINAMOS ANGLIES NEUTRALUMO PRAKTIKOS TECHNOLOGIŠKAI PAŽANGIOSE ŠALYSE: ŽIEDINĖS EKONOMIKOS PERSPEKTYVA

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Santrauka. Globalus atšilimas išlieka nuolatine problema, kuriai spręsti reikalingi plataus masto sprendimai. Pernelyg didelė priklausomybė nuo neatsinaujinančių išteklių ir spartėjanti industrializacija lėmė augančius atliekų kiekius, todėl būtina kurti veiksmingas strategijas, iki 2030 m. leidžiančias sumažinti CO_2 emisijas ir iki 2050 m. pasiekti nulinės taršos tikslą. Siekiant anglies neutralumo itin svarbi žaliųjų praktikų ir žiedinės ekonomikos ryšio analizė. Tyrime nagrinėjama, kaip žalioji logistika ir dirbtinis intelektas formuoja žiedinę ekonomiką, atsižvelgiant į tokius veiksnius kaip ekonomikos augimas, moksliniai tyrimai ir eksperimentinė plėtra, aplinkosaugos mokesčiai ir atsinaujinanti energija. Tyrimas apima technologiškai pažangias ekonomikas 2000–2023 m. laikotarpiu. Tyrime taikytas Momentų metodo kvantilių regresijos (MMQR) požiūris. Analizės rezultatai atskleidė, kad dirbtinis intelektas teigiamai veikia žaliąją logistiką, tačiau neturi statistiškai reikšmingo poveikio žiedinės ekonomikos praktikoms tirtoje imtyje. Taip pat nustatyta, kad atsinaujinantys ištekliai ir moksliniai tyrimai bei eksperimentinė plėtra tiesiogiai neveikia šalies ekonomikos augimo, tačiau ekonomikos augimas ir aplinkosaugos mokesčiai reikšmingai veikia žiedinės ekonomikos principus. Siekiant patikrinti rezultatų patikimumą, papildomai taikytas įgyvendinamas apibendrintųjų mažiausių kvadratų metodas (FGLS), kuris patvirtino MMQR išvadas. Remiantis tyrimo rezultatais, politikos formuotojams rekomenduojama stiprinti paramą tvarioms žaliųjų logistikos operacijoms ir dirbtinio intelekto technologijoms, siekiant pasiekti anglies neutralumo tikslus.

Reikšminiai žodžiai: anglies neutralumas; pramonė 4.0; žalioji tiekimo grandinė; žiedinė ekonomika; technologiškai pažangios šalys.