Pathways to carbon neutrality in major exporting countries: the threshold effect of digital transition

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Abstract
By investigating the threshold effect on carbon emission from the perspective of digital transformation, this paper collects the panel data of 29 world’s major exporting countries from 2000 to 2019 to explore the impact of energy consumption on CO₂ discharge by constructing a multi-variate threshold model. We further decompose digital transition into several indicators of digital infrastructure development, digital trade competitiveness, and digital technology exploitation. The key findings demonstrate that energy consumption exert a significant threshold effect on carbon emissions. When per capita energy usage is selected as the core explanatory variable, digital infrastructure and digital technology exploitation display significant single threshold effect. Likewise, when the proportion of renewable energy consumption is considered the key independent variable, digital trade competitiveness and digital technology exploitation also present significant single threshold impact. Overall, the deeper the digital transformation, the weaker the promotion effect of per capita energy consumption on carbon emissions, and the stronger the influence of the proportion of renewable energy on CO₂ abatement. Robustness test confirms that the conclusions of this study are stable and consistent. Policymakers ought to better utilize the opportunities that digital transition offer for energy conservation and carbon neutrality realization. The specific policy implications include the following: (1) raise the scale of the application of renewable energy in digital infrastructure, (2) ameliorate the assessment system for the utilization of renewable energy in the digital industry, (3) elevate the incentive mechanism for boosting the adoption of clean energy during digitalization, (4) steadily advance the digital transition and refinement of industrial structure, and (5) high-income developed economies should help low- and middle-income developing countries accelerate the development of low-carbon economy.

Keywords Emissions reduction · Energy consumption · Digital transformation · Threshold effect · Carbon neutrality

Introduction
The global problem of climatic warming is one of the major challenges facing human society, and the greenhouse gas emission represented by carbon dioxide is widely recognized as the main inducement. Since the end of last century, international environmental protection agencies have been trying to promote cooperation among countries and look forward to reaching a consistent emission reduction strategy (Aydin et al. 2019). Especially since the COVID-19, the importance of keeping in harmony with nature and preventing epidemic disasters from entering into the climate disaster has gradually become an international consensus. The carbon peaks and carbon neutrality targets in various countries have been obviously accelerated. With the deepening of economic globalization, production segments scattered all over the world are integrated into the global production division system. Under the current background of division of labor, developed countries occupy the upstream link of the global value chain by virtue of technological advantages, transfer high carbon emission industries, realize their own carbon emission abatement, but increase the pressure of carbon emission in downstream developing countries. In the field of import and export trade, countries are gradually implementing low-carbon import policies, and international low-carbon barriers are gradually increasing. In recent decades, environmental problems such as the sharp elevation of carbon
emissions and the greenhouse effect have been deteriorating in the world’s leading exporting nations (Table 1 and Fig. 1). The shale oil production of the USA ranks first in the world, as well as the per capita car ownership. Multiple factors keep its per capita carbon emission ranking high in the world all along. Although Australia has a small population, benefiting from the rapid economic development in recent years, the rapid growth of mining and aquaculture leads to the steady climb of per capita carbon emissions. Australia was the largest per capita carbon emitter in the world from 2009 to 2011 (from 18.21 to 17.26 metric tons). Saudi Arabia took the first place during 2015 and 2016 (17.69 and 17.16 metric tons). As the world’s largest oil producer and exporter, Saudi Arabia is mainly engaged in oil production and smelting, and then exported to other countries, which discharges huge volume of CO₂. The development of low-carbon and energy-saving technologies has become a consensus of all countries.

Carbon neutrality means that enterprises, groups, or individuals calculate the total amount of greenhouse gas emissions directly or indirectly within a certain period of time; offset their own carbon dioxide emissions through afforestation, energy conservation, and emission reduction; and realize zero carbon dioxide emissions. The goal of carbon neutrality is not only the internal requirement for the world economy to achieve sustainable and high-quality development, but also the inevitable choice to promote the construction of a community with a shared future for mankind and the scientific judgment of comprehensively considering the ability of climate mitigation and adaptation (Rehman et al. 2021). In the meantime, the importance of digital technology

| Code | Country          | Code | Country        | Code | Country         |
|------|------------------|------|----------------|------|-----------------|
| 1    | Australia (AUS)  | 11   | Ireland (IRL)  | 21   | South Korea (KOR) |
| 2    | Austria (AUT)    | 12   | Italy (ITA)    | 22   | Spain (ESP)     |
| 3    | Belgium (BEL)    | 13   | Japan (JPN)    | 23   | Sweden (SWE)    |
| 4    | Brazil (BRA)     | 14   | Malaysia (MYS) | 24   | Switzerland (CHE) |
| 5    | Canada (CAN)     | 15   | Mexico (MEX)   | 25   | Thailand (THA)  |
| 6    | China (CHN)      | 16   | Netherlands (NLD) | 26   | Turkey (TUR)   |
| 7    | France (FRA)     | 17   | Poland (POL)   | 27   | UK (GBR)        |
| 8    | Germany (DEU)    | 18   | Russian Federation (RUS) | 28   | USA (USA)      |
| 9    | India (IND)      | 19   | Saudi Arabia (SAU) | 29   | Vietnam (VNM)  |
| 10   | Indonesia (IDN)  | 20   | Singapore (SGP) |      |                 |

**Table 1** Twenty-nine major exporting economies and their codes

**Fig. 1** Box plot of per capita CO₂ emissions for the major exporting economies
to the development of green and low-carbon industry is becoming increasingly prominent. Digital technology can drive energy conservation and emission control of traditional industries and play a key role in achieving the goal of carbon neutrality. At present, countries around the world are accelerating the development of new generation of information technology to promote the Internet, big data, artificial intelligence (AI), fifth generation mobile communication (5G), and other emerging technologies to deeply integrate with green and low-carbon industries. Building a green network is a systematic project (Aydin and Esen 2018a). On the energy supply side, new energy solutions need to focus on reducing carbon emissions from energy introduction. On the energy consumption side, green sites and green data centers need to be built to significantly reduce carbon emissions from energy usage. Digital technology is integrating with machine vision, AI, and big data. The combination of technologies not only accelerates the digital transformation of high energy consumption industries such as energy, metal smelting, manufacturing, and transportation, but also has the most outstanding achievements in energy conservation and consumption reduction. This research has great importance and differs from the existing studies in that we explore the energy conservation and emission reduction effect from the perspective of digital transition. Therefore, it is necessary to comprehensively promote the organic incorporation and coordination with carbon peak and carbon neutrality in the frontier fields of social and economic development featured by digital economy. It is of great significance for digital economy to help achieve carbon neutrality.

The remainder of the thesis framework is organized in the following form. The “Literature review” section reviews several strands of relevant literature to interpret the contribution of this study; the “Theoretical model construction” section constructs the mathematical model to theoretically expound the relationship between digital transition and carbon neutrality; the “Methodology and data” section illustrates the methodology and variable selection to intuitively observe the data feature; the “Empirical research” section conducts the econometric technique and discusses the results to compare to existing studies; The “Conclusions and policy implications” section concludes the findings and proposes policy suggestions.

Literature review

Study on the environmental efficiency in open economies

At present, the theories on the relationship between trade openness and environmental pollution are mainly grouped into the following three categories.

The first is the beneficial theory of trade, which believes that the improvement of trade openness will eventually ameliorate the ecological system and reduce environmental pollution. The empirical results of some researchers strongly support this view. A number of scholars found that the rise of trade openness is not only advantageous to advancing the carbon emission performance of manufacturing industry and reducing China’s carbon emission but also plays a certain role in promoting carbon emission abatement in economically developed countries (Ren et al. 2014; Aydin and Esen 2018b; Sun et al. 2019; Wang et al. 2020). Some studies have also verified that trade openness will reduce carbon emissions. By using threshold regression technique to investigate China’s inter-provincial panel data, Lin and Sun (2010) reported that trade openness has a significant positive effect on the growth of GTFP, but this impact presents nonlinear characteristics and spatial heterogeneity due to the threshold effect of foreign direct investment and human capital level.

The second is the harmful theory of trade, whose representative theories mainly include “pollution paradise hypothesis” and “race to the bottom hypothesis.” Erüç and et al. (2016) and Hu et al. (2018) believed that developing countries will attract developed countries to migrate pollution intensive enterprises to their countries by reducing their environmental regulation standards, develop their domestic economy, and enhance their trade competitiveness at the expense of the environment. Shaikh et al. (2020) further verified the harmful trade theory and believed that trade opening would promote carbon emissions. Similar conclusions were also arrived at regarding India’s trade-carbon emission nexus (Kanjilal and Ghosh 2013; Sinha and Shahbaz 2018; Adamu and Shafiq 2019; Wang and Yang 2020). Based on the panel smooth transition regression model, the conclusion of Andersson (2018) and Jiang et al. (2019) implied that import and export aggravate environmental pollution.

The third is neutral theory of trade. Lau et al. (2014) and Kim et al. (2019) divided the impact of trade on the environment into three types: scale effect, technology effect, and structure effect. Scale effect refers to the environmental deterioration caused by the expansion of economic scale; technology effect signifies that the means used in the normal production and operation process affect the environment; structure effect represents the impact of industrial structure on the environment. But whether trade affects the environment positively or negatively depends on the sum of these three effects (Li and Hewitt 2008; Marques et al. 2013; Zhang and Zhang 2018). The study of Fernández-Amador et al. (2016) and Wang et al. (2020) discussed the green economic growth of trade liberalization from different viewpoints and uncovered that with the cooperation of domestic research and development (R&D), import can facilitate the progress of green technology, while export exerts inhibitory impact. The empirical research on the influence of
processing trade on carbon emissions was conducted by Gozgor (2017), Meng et al. (2018), and Li et al. (2020), whose results manifested that there is a significant inverted U-shaped curve relationship between processing trade and carbon emission efficiency.

**Study on the impact of digital transition on carbon neutrality**

Alongside the advancement of computer technology, the impact of digital economy on environment and sustainable development has aroused extensive controversy in the academia.

First, digitization can catalyze carbon neutrality. Ciocoiu (2011) documented that in the context of the accelerated deterioration of the global ecological environment, the global digital network can connect all regions of the world and cultivate new social norms. In the long run, it may play a profound role in environmental protection. Fourcade and Kluttz (2020) clarified that digitization helps to realize the ecological modernization of production processes, which can ensure the efficient utilization of resources and the sustainable development of national and global economy. The progress of Internet technology has boosted the resource utilization efficiency and the widespread use of new environmental preservation technologies and elevated the prevention and control of pollutant discharge (Lopez et al. 2019; Li et al. 2021a, b; Aydin et al. 2022). Bolla et al. (2010) reported that digital transformation and carbon neutrality are synergistic. On the one hand, digital transformation can effectively promote energy conservation and emission reduction of the global economy. On the other hand, carbon neutrality can also help the digital economy achieve green and sustainable development. Given the merits of the Internet platform, enterprises are conducive to their own product innovation and the transformation of low-carbon production mode (Wahab et al. 2021; Wen et al. 2021).

Second, although digital transformation has great potential in improving the environment, the negative impact of digital economy on the environment should not be ignored (Shahbaz et al. 2017; Park et al. 2018). Zhou et al. (2021) claimed that digitization is not favorable to the development of low-carbon or sustainable economy by collecting and studying the data of the top 10 countries in the world. In addition, the implementation of the global green growth goal needs to control the spread speed of digital transformation. Other researches (Sbia et al. 2014; Schulte et al. 2016) have asserted that the development of digital technology has heightened the demand for energy and aggravated ecological condition. Industrial digitization leads to more energy depletion and carbon emissions (Wang and Wang 2021). Granell et al. (2016) unveiled that if the number of Internet users increased by 1%, the per capita power use would increase by 0.026%. Meanwhile, according to Zhou et al. (2019), the energy usage of the information technology industry and the intermediate investment in contaminative products result in massive carbon emissions. Avom et al. (2020) uncovered a one-way causal relationship between ICT and energy consumption in Sub-Saharan Africa.

Finally, some studies stated that there is a nonlinear relationship between digital transformation and carbon neutrality. Kovacikova et al. (2021) validated that there is an inverted U-shaped curve relationship between digital transformation and SO2 emission by examining China’s provincial panel data. Digital transformation has a positive effect on carbon neutrality in developed areas of China, whereas it has a significant negative impact within backward regions. Digital economy raises carbon emissions in the early period and lessens pollutant discharge in the later phase (Hong 2017; Latif et al. 2018; Li et al. 2021a, b).

**Current literature gap and contribution of this study**

The preceding literature has laid a solid foundation for the research of this article. By sorting out the extant studies, we find that scholars mostly shed light on the influencing factors of carbon emissions. The influence of digital technology on economic development has been deeply concerned by scholars, but systematic researches on how digital transformation affects carbon neutrality is deficient. To the best of our knowledge, the study on the impact of digital economy and digital transition on carbon emissions is still in the initial stage, the number of literature is relatively small, and most investigations are based on qualitative analysis, while quantitative researches are insufficient.

To sum up, the existing literature on carbon emission and carbon neutrality rarely involves the measurement of threshold effect of digital transition. The digital economy is mostly estimated by single index method, which is difficult to accurately describe the actual change level of digital transformation. Few studies mainly discussed the impact of information and communication technology (ICT) on carbon emissions. Compared with ICT, the comprehensive digital transition evaluation index can more completely reflect the effect of digital technology on economy and society, business model, production, and transaction mode. The “Internet plus” development mode has been the indispensable route for the international society to achieve industrial upgrading and green manufacturing.

Therefore, the contribution of this paper is reflected in several noteworthy places. First of all, we focus on the top exporting countries who have been the main carbon emitters for the last few decades. Moreover, this paper enriches the theoretical rationale on the effect of digital transition on carbon neutrality. Additionally, we develop three types of indicators to systematically measure the features of digital
transition, which encompasses digital infrastructure development, digital trade competitiveness, and digital technology exploitation. Lastly, based on quantitative research, this paper constructs a panel threshold model to capture the phased characteristics of the impact of digital transformation on carbon emission and carbon neutrality.

Theoretical model construction

Production technology assumption under open economy

The general equilibrium model of trade and environment proposed by Antweiler et al. (2001) holds that the scale effect of trade openness will increase a country’s carbon emission, while the technology effect will help reduce carbon emission. In the context of trade liberalization and production globalization, supposing an open economy uses two factors of production capital (K) and labor (L) for production, the two finished products are X and Y. X is a polluting product that produces carbon emissions, and Y is a clean product that does not yield carbon emissions. It is assumed that the prices of X and Y are P_X and P_Y. In terms of production technology, the return on scale of the two products remains unchanged. In terms of factor input, it is assumed that there are only capital and labor inputs in the economy, and the supply elasticity is zero. Within the economy, the capital interest rate is r, and the wage level is w. Based on the analysis of Copeland and Taylor (2004) and the factor endowment hypothesis, we deduce that X is a capital-intensive product and Y is a labor-intensive product. According to the above assumptions, the production functions of products X and Y can be expressed as:

$$X = (1 - \theta)F(K_x, K_y)$$  \hspace{1cm} (1)

$$Y = H(K_x, L_y)$$  \hspace{1cm} (2)

$$C = \mu(\theta)F(K_x, L_y)$$  \hspace{1cm} (3)

where F and H are increasing homogeneous concave production functions. F represents the ideal maximum output of the enterprise producing X, that is, the maximum output when all elements of department X are input into product production. \(\theta\) reflects the resource allocation of carbon emission abatement in department X, and 0 ≤ \(\theta\) ≤ 1. \(M(\theta)\) reflects the intensity of carbon emission control, which is the function of proportion of factor input. It reflects that the higher the proportion of digital factor input in carbon emission control, the lower the actual level of carbon emission under the given ideal output level. According to Formula (1), the output of product X is determined by the potential maximum output of product X and the proportion of digital elements input. The production of product X is a decreasing function of \(\theta\). But the carbon emission reduction function \(\mu(\theta)\) will also be affected by technology level A. We set the carbon emission abatement intensity function of sector X as follows:

$$\mu(\theta) = \frac{1}{A}(1 - \theta)^{1/\alpha}$$  \hspace{1cm} (4)

where \(\alpha\) is a function parameter and 0 < \(\alpha\) < 1 and A represents the digital technical level of carbon emission reduction. Along with the augmentation of A, the technical level of carbon emission abatement in department X is steadily elevated. This means that when the ratio of input factors stays invariant, the carbon emission reduction intensity of the industry climbs with the enhancement of technological progress. By introducing the carbon emission intensity function (4) into the carbon emission production function (3), we can get:

$$C = \frac{1}{A}(1 - \theta)^{1/\alpha}F(K_x, L_y)$$  \hspace{1cm} (5)

At this time, the production function of product X can be expressed as:

$$X = (AC)^{1/a}[F(K_x, L_y)]^{1-a}$$  \hspace{1cm} (6)

The above formula indicates that product X can be deemed as production by two input factors of carbon dioxide emission C and potential output F, which meets the characteristics of homogeneous function with constant return to scale.

Theoretical effect model of digital transition and carbon neutrality

On the basis of Walter and Ugelow (1979) and Esty and Dua (1997), this paper constructs a theoretical model of digital transformation on carbon neutrality. In this model, creative destruction is the core driving force to promote green technology innovation and carbon neutrality. The assumptions of the model are listed below. Enterprises are allowed to enter and exit; green technology innovation that helps carbon neutrality comes from new enterprises or existing enterprises; an enterprise is a collection of a series of production units; enterprises expand through green technology innovation on a product line, so as to replace the original enterprises on the product line. We assume that the value of the enterprise with n types of products in the period t satisfies the Bellman equation, then:

$$rK_t(n) - K_t(n) = \max_{i \geq 0} \left\{ nK_t - w_iK_{i+1}^0 + n\sum_{i=0}^n [K_t(n + 1) - K_t(n)] + n\sum_{i=0}^n [K_t(n + 1) - K_t(n)] \right\}$$  \hspace{1cm} (7)
where \( K(n) = n\kappa Y \), wage rate \( w = W/Y \), \( \kappa = e^{-\lambda w\xi} / (1 + e^{-\lambda w}) \). \( \pi \) is profit, \( \theta \) is the reciprocal of green technology innovation on the elasticity of digital R&D personnel, and \( \lambda \) is scale parameter. The green technology innovation intensity of existing enterprises \( z_i \) can be obtained from Eq. (7):

\[
z_i = (\frac{\kappa}{\theta \lambda w})^{1/(\theta-1)} \leq \left( \frac{\sigma\kappa}{\lambda w} \right)^{1/\theta}
\]

(8)

A potential new enterprise employs \( \delta \) digital researchers and carries out digital technology innovation with factor \( \zeta > 1 \). The assumption that the market is free to enter signifies that the value of new enterprises \( K(1) \) must be equal to the cost of green technology innovation \( \omega \). We set the market entry rate of each product equal to \( z_e \). Since the creative destruction of each product is equivalent to the market entry rate of new enterprises plus the creative destruction rate of existing enterprises, thus \( x = z_i + z_e \). From Eq. (7), we can get:

\[
(\tau + z_e)\kappa = \pi - \lambda w\frac{\sigma\kappa}{\lambda w}, \quad z_e = \frac{\pi}{\omega\delta} - \sigma - \tau
\]

(9)

where \( \rho \) is the subjective discount rate of consumers. Before the realization of digital transformation, existing enterprises cannot invest more than \( \sigma \) times their market value in green technology innovation. If we assume \( \theta = 0.5 \), that is, the elasticity of green technology innovation on digital R&D personnel is 2, then the balanced growth rate is:

\[
g = x\ln\zeta = (z_i + z_e)\ln\zeta = \left( \frac{\pi}{\omega\delta} - \sigma - \tau + \frac{\delta^2}{\lambda^2}\sigma^2 \right)\ln\zeta
\]

(10)

It can be seen from the above formula that there is a non-linear relationship between digital transformation and green technology progress.

**Methodology and data**

**Econometric techniques**

**Cross-sectional dependence**

When using panel data model for econometric analysis, there will be strong correlation between sections in some cases, and its judgment basis is that there is cross-sectional correlation between error terms. The reason is that the common economic impact and unidentified components affecting the dependent variables are not introduced as independent variables, but become part of the error term, which will lead to biased and inconsistent model estimates. Therefore, the cross-sectional dependence test is needed before estimating the model.

**Unit root test**

This study collects macroeconomic time series data from multi-countries. In most economic fields, the mean and variance of macroeconomic time series change with time. Constructing regression model with non-stationary economic variables will bring spurious regression. Therefore, it is an issue that must be tackled to test the instability of economic variables in this paper. Considering that the disturbance term may have autocorrelation, Levin et al. (2002) introduced a high-order difference lag term:

\[
\Delta y_{it} = \delta y_{i,t-1} + z_i y_{it} + \sum_{j=1}^{p_i} \theta_j \Delta y_{i,t-j} + \epsilon_{it}
\]

(11)

where \( \delta \) is the common autoregressive coefficient, i.e., the common root; the lag order \( p_i \) of different individuals can be different; \( \{\epsilon_{it}\} \) is a stable process of autoregressive moving average model; \( \epsilon_{it} \) of various individuals are independent of each other, but heteroscedasticity is allowed. By introducing a sufficiently high-order differential lag term, we can ensure that \( \epsilon_{it} \) is white noise.

**Cointegration test**

Cointegration is a statistical description of the long-term equilibrium relationship of non-stationary economic variables. One time series might be non-stationary alone, but the series of two or more series after linear combination would be stable. The stationary series after linear combination has a long-term stable equilibrium relationship, which is called cointegration relationship. Variables with cointegration relationship in the short term may break away from this cointegration relationship, but they will still return to this cointegration equilibrium relationship after long-term changes. The stationary linear group established in this paper is the relationship between more than two economic variables, so we adopt the Johansen cointegration test, which is better than the EG (Engle-Granger) two-step test.

For \( k \) time series \( y_{it} = (y_{1t}, y_{2t}, ..., y_{kt})' (t = 1, 2, ..., n) \), the components of \( k \) dimensional vector \( y_i \) are called \((d, b)\) order cointegration, which is recorded as \( y_{i} \sim CI(d, b) \). If each component of \( y_i \) is \( y_{it} \sim I(d, b) \), there is a non-zero vector \( \beta \) (also known as cointegration vector), so that \( \beta' y_{it} \sim I(d - b), 0 < b \leq d \).

If the matrix composed of the cointegration vector of \( y_i \) is \( A \), and the rank of matrix \( A \) is \( r \), then \( 0 < r < k \). For the following model \( y_i = A_1 y_{i-1} + A_2 y_{i-2} + ... + A_p y_{i-p} + B x_i + U_i \), \( y_i \) in the formula is a non-stationary variable, \( A_1, A_2, ..., A_p \) is a parameter matrix of order \( k \times k \), \( x_i \) is a stable \( d \) dimensional exogenous vector, representing deterministic terms such as trend term and constant term, and \( U_i \) is \( k \) dimensional.
random error vector. The below formula is obtained after differential transformation:

\[ \Delta \ln y_t = \prod_{i=1}^{p-1} \ln y_{t-i-1} + \sum_{i=1}^{p-1} \tau_i \Delta y_{t-i-1} + B \ln x_t + U_t \]  

(12)

where \( \prod = \sum_{i=1}^{p} A_i - I \), \( \tau_i = - \sum_{j=p+1}^{p} A_j (i = 1, 2, ..., p - 1) \). \( \Pi \) refers to compressed matrix. Using the eigenvalue and trace statistic of Johansen cointegration test, let the characteristic root of matrix \( \Pi \) be \( \phi_1 > \phi_2 > ... > \phi_k \). The null hypothesis \( H_{r0} : \phi_r > 0, \phi_{r+1} = 0 \) is that there exists at most \( r \) cointegration vectors, and the alternative assumption \( H_{r1} : \phi_{r+1} > 0 \) is that there exists \( r \) cointegration vectors \((r = 0, 1, 2, ..., k - 1)\), and the corresponding test statistics are:

\[ \omega_r = -n \sum_{i=r+1}^{k} \ln (1 - \phi_i) \quad (r = 0, 1, 2, ..., k - 1) \]  

(13)

\( \omega_r \) stands for the eigenvalue and trace statistic, and the significance of the statistics are tested in turn. When \( \omega_r \) is less than the critical value, then accepting the null hypothesis \( H_{r0} \), which indicates that there exists \( r \) cointegration vectors. When \( \omega_r \) is greater than the critical value, then rejecting the null hypothesis \( H_{r0} \), which implies that there exists at least \( r+1 \) cointegration vectors.

### Threshold test

In previous empirical studies, when it is necessary to investigate the nonlinear structural mutation of the explanatory power of one explanatory variable on the explanatory power of the explained variable with the change of another explanatory variable, the model is usually set up by means of interaction-term test, grouping test, or the introduction of dummy variables. The grouping test sets the segmentation point through subjective experience, while the interaction-term test is limited by the uncertainty of the form of cross items. Neither of them can test the significance of threshold effect. The threshold regression model proposed by Hansen (2000) can overcome the shortcomings of the above two methods. It can not only accurately estimate the threshold value, but also complete the significance test. Unlike the traditional subjective grouping, panel threshold method does not need to preset the threshold based on theoretical value or experience. Threshold regression groups the sample data endogenously, which eliminates the subjectivity, and can test the significance after estimating the threshold value of the sample data. Moreover, this method can be further extended to the multi-threshold model based on the single threshold model. Also, panel threshold can estimate the threshold value by integrating the two-dimensional information advantages of cross-sectional individuals and continuous time series. Therefore, this paper employs this technique to build a threshold model of the impact of energy consumption on carbon neutrality with digital transformation as the threshold variable.

\[ CE_{it} = \mu_i + a_i \ln X_{it} + a_2 EC_{it} \times I (DT_{it} \leq \gamma_1) + a_3 EC_{it} \times I (DT_{it} > \gamma_1) + \varepsilon_{it} \]  

(14)

\[ CE_{it} = \mu_i + b_i \ln X_{it} + b_2 REN_{it} \times I (DT_{it} \leq \gamma_1) + b_3 REN_{it} \times I (DT_{it} > \gamma_1) + \varepsilon_{it} \]  

(15)

where \( i, t \) are country and year, respectively; \( \mu_i \) is constant term; \( X \) is control variables matrix; \( I(\cdot) \) is indicator function; if the expression in parentheses is true, the value is 1; otherwise, the value is 0; \( \gamma \) is threshold to be estimated. Considering that there might be multiple thresholds, we further set the multi-threshold model as follows.

\[ CE_{it} = \mu_i + a_i \ln X_{it} + a_2 EC_{it} \times I (DT_{it} \leq \gamma_1) 
+ a_3 EC_{it} \times I (\gamma_1 < DT_{it} \leq \gamma_2) 
+ a_4 EC_{it} \times I (DT_{it} > \gamma_2) + \varepsilon_{it} \]  

(16)

\[ CE_{it} = \mu_i + b_i \ln X_{it} + b_2 REN_{it} \times I (DT_{it} \leq \gamma_1) 
+ b_3 REN_{it} \times I (\gamma_1 < DT_{it} \leq \gamma_2) 
+ b_4 REN_{it} \times I (DT_{it} > \gamma_2) + \varepsilon_{it} \]  

(17)

(1) Threshold effect test

In threshold estimation, two problems need to be solved. One is to estimate the threshold \( \gamma \) and the regression parameters of the important variable DT. The second is to examine the estimated threshold value, where threshold \( \gamma \) and the key investigation variable DT are obtained by minimizing the residual estimation value of ordinary least squares estimation under the assumed threshold number. After obtaining the corresponding parameter estimation, it is necessary to verify the significance of threshold effect and the confidence interval of the estimated threshold value. The null hypothesis of the significance test of threshold effect is \( H_0 : \beta_1 = \beta_2 \), that is, there is no threshold effect, and the alternative hypothesis is \( H_1 : \beta_1 \neq \beta_2 \); in other words, there exists threshold effect. The test statistics are:

\[ F_1 = \frac{S_0 - S_1 (\hat{\gamma})}{\hat{\sigma}^2} = \frac{S_0 - S_1 (\hat{\gamma})}{S_1 (\hat{\gamma})/n(T-1)} \]  

(18)

where \( S_0 \) and \( S_1 (\hat{\gamma}) \) are the sum of squares of residuals under the null hypothesis and threshold estimation, respectively, and \( \hat{\sigma}^2 \) is the variance of residuals.
under threshold estimation. Since the threshold under the null hypothesis cannot be identified, \( F_1 \) statistic is non-standard distribution, but the asymptotic distribution of likelihood ratio (LR) test can be simulated by “self bootstrap,” and the \( p \)-value constructed based on this also has asymptotic effectiveness. If the \( p \)-value is less than the critical value we set, then we can reject the null hypothesis and assert that the threshold effect is significant; otherwise, we can claim that there is no threshold effect in the model.

(2) Consistency test between threshold estimate and real value

For the consistency test of threshold value, the null hypothesis is \( H_0: \hat{\gamma} = \gamma_0 \), and the alternative hypothesis is \( H_1: \hat{\gamma} \neq \gamma_0 \). Under the premise of threshold effect, \( \hat{\gamma} \) is a consistent estimator of \( \gamma_0 \), but its asymptotic distribution is non-standard. Nevertheless, the non-rejection region of \( \gamma \) can be established by LR statistics. The LR test statistics are constructed as:

\[
LR_1(\gamma) = \frac{S_1(\hat{\gamma}) - S_1(\hat{\gamma})}{\sigma^2}
\]

(19)

where \( S_1(\gamma) \) is the sum of squares of residuals under unconstrained conditions and \( LR_1(\gamma) \) is also a non-standard distribution. When \( LR_1(\gamma) > c(a) \), the null hypothesis is rejected, and it is considered that the threshold estimated value was not equal to its true value, in which \( c(a) = -2\ln\left(1 - \sqrt{1 - a}\right) \). \( a \) is the significance level. At the same time, LR test chart could be drawn to more visually observe the confidence interval and rejection region of the threshold value. In order to determine whether there are multiple thresholds in the model, it is necessary to inspect the significance and confidence interval of the next threshold in light of the single threshold model. If the test fails, we can accept the single threshold assumption; otherwise, to proceed to more threshold tests, and the like.

(3) Fixed effect threshold regression model

The research objects of panel threshold model include T periods and n individuals. For panel data \( \{y_{it}, x_{it}, q_{it} : 1 \leq i \leq n, 1 \leq t \leq T\} \), where \( n \) is the individual and \( T \) represents the time. Hansen (1999) investigates the fixed effect threshold regression model and utilizes with-in transformation to eliminate the fixed effects:

\[
y_{it} = \mu_{it} + \beta_1 x_{it} + \varepsilon_{it}, \text{if } q_{it} \leq \gamma
\]

(20)

\[
y_{it} = \mu_{it} + \beta_1 x_{it} + \varepsilon_{it}, \text{if } q_{it} > \gamma
\]

(21)

In the above formulas, \( q_{it} \) is the threshold variable (which can be an explanatory variable or not), \( \gamma \) is the threshold value to be estimated, and \( \varepsilon_{it} \) is subject to independent identically distributed. Using the indicative function \( I(\cdot) \), the equations can be expressed as:

\[
y_{it} = \mu_{it} + \beta_1 x_{it} \cdot I(q_{it} \leq \gamma) + \beta_1'' x_{it} \cdot I(q_{it} > \gamma) + \varepsilon_{it}
\]

(22)

Variables selection

(1) Explained variable

Carbon emission (CE)

Carbon emission is an inevitable by-product of energy consumption in the process of modern economic development. Carbon emission is a double-edged sword, which not only reflects the scale of economic activities to a great extent, but also produces greenhouse effect. The fundamental to promoting carbon neutrality is to reduce carbon emissions (Khan et al. 2020). The key to tackle this problem is to lead high-quality economic growth with the concept of green innovation and jointly uplift economic and social development with deep decarbonization. Trade has been a momentous driver for world carbon emissions. Some developing countries are becoming a refuge for the transfer of international high carbon emission industries. Under a certain pollution tax rate, with the evolution of trade liberalization in developed and developing countries, the environmental problems of various countries have shown divergence (Dou et al. 2021). This paper gathers data of per capita carbon emissions to depict the environmental situation of various countries (unit: metric tons).

(2) Core explanatory variables

Energy consumption (EC)

Integrating the carbon neutrality goal into the coordinated high-quality development process of economy, society, and ecological environment of export-oriented countries is of far-reaching significance to realize the green and low-carbon growth of the global economy. Among the major exporting nations, the proportion of coal and oil consumption in primary energy consumption is higher than the global average, and the carbon emission chiefly comes from the energy consumption with a high total volume. Carbon neutrality should be attained by restraining the total energy consumption and facilitating the upgrading of energy structure (Shahzad et al. 2017). Therefore, this paper chooses per capita energy consumption as one of the core explanatory variables (unit: kg of oil equivalent). Renewable energy consumption (REN)
The more successful the energy transformation is, the sooner the carbon peak goal is achieved, and the smaller the cost paid by the whole society in the process of realizing the long-term carbon neutrality goal. Therefore, energy transition is the key procedure to attain the goal of carbon neutrality and even transform green development into new comprehensive national strength and international competitive advantage. The core content of international low-carbon energy transformation in the coming decades is to ceaselessly heighten the proportion of clean energy, which is mainly featured by the progressive decline of carbon emissions per unit of GDP (Dogan and Seker 2016). In this paper, the proportion of renewable energy consumption is selected to measure the importance of energy structure transformation (unit: %).

(3) Threshold variables

Digital infrastructure development (INRT)

The innovation of enterprise organization and management supported by the popularization of Internet can reduce the cost of information search, product transportation and order tracking, as well as raise the efficiency of enterprise operation, production, and innovation activities. Internet technology elevates the advancement of total factor productivity of manufacturing industry by lowering unit transaction costs, promoting industrial integration, and ameliorating energy consumption structure (Ren et al. 2021). In the academia, however, there are not publicly recognized indicators to estimate the development level of digital infrastructure. Numerous studies embedded digital infrastructure in the digital economy indicator system, taking the number of Internet users, the number of mobile phone users, the penetration rate of fixed broadband and fixed telephone, and the coverage rate of mobile network as the measurement indicators (Haseeb et al. 2019). Therefore, this paper selects the proportion of Internet users in the total population to measure the perfection of digital infrastructure (unit: %).

Digital trade competitiveness (ICT)

As the extension and application of digital economy, digital trade is characterized by digital knowledge and information as key production factors, transmission, and even transaction with the help of modern information network (Zhang 2012). Digital trade is a trade activity for the purpose of uplifting the performance of traditional economic activities and upgrading economic structure. The rise of digital trade facilitates and accelerates the dissemination and transaction of knowledge and information, catalyzes technological progress, and boosts economic efficiency (Shahbaz et al. 2019). These digital knowledge and information are rapidly spread and traded through Internet communication, which can finally optimize resource allocation and promote energy conservation and emission regulation. This paper adopts the proportion of ICT product exports in total exports to measure the competitiveness of digital trade (unit: %).

Digital technology exploitation (PAP)

Digital technology is the core of digital economy and the main engine to motivate the growth of digital economy. Similarly, the realization of carbon neutrality is inseparable from technological innovation. Among them, the scientific research level of digital technology innovation exerts the largest positive effect due to its small time lag in the application of achievements, which can assist enterprises achieve data innovation and cleaner production (Li et al. 2018). The digital scientific research strength contained in the number of scientific and technological papers is the source power to optimize the industrial structure of manufacturing industry. Under the effective achievement transformation mechanism of scientific research institutions, the digital technology innovations are convenient for immediate implementation and can be promptly applied to the green and low-carbon production of manufacturing industry (Kunkel and Matthess 2020). In our study, the number of scientific and engineering papers published is the proxy for the level of digital technology exploitation.

(4) Control variables

If we only study the impact of energy consumption on carbon dioxide emissions intensity, although it is easy to identify its direct effect, the neglect of the role of other essential explanatory variables on carbon emission may cause instability and bias of the estimation results. In order to avoid the above problems, combined with the previous works (Fuchs 2008; Naranpanawa 2011; Long et al. 2018; Wang and Han 2021), other control variables affecting carbon emissions are incorporated in the model for analysis. Specifically, this paper employs urbanization rate (URB) measured by the proportion of urban population in total population, patent application volume (PAT), merchandize trade volume (TRD) in unit of proportion to GDP, and per capita gross domestic product (GDP) in unit of constant 2010 US$.

Data source and feature

Given that the major exporting countries consist of developed countries and emerging industrialized countries, which account for a large proportion of the world’s total carbon emissions. after entering the new century, some countries have successively launched carbon neutrality plans. On account of the availability and consistency of data, this paper adopts the panel data of 29
major exporting economies (excluding Hong Kong region due to lack of data) in the world from 2000 to 2019, and the data used stem from the WDI database of the World Bank. In order to eliminate the possible heteroscedasticity, some data have been transferred into their natural logarithmic form. The statistical description and correlation matrix of sample data are exhibited in Table 2.

The world’s top export-oriented economies include both developed countries and a considerable number of developing countries. The developed countries contain AUS, AUT, BEL, CAN, FRA, DEU, IRL, ITA, JPN, NLD, SGP, KOR, ESP, SWE, CHE, GBR, and USA. The developing countries consist of BRA, CHN, IND, IDN, MYS, MEX, POL, RUS, SAU, THA, TUR, and VNM. The developed and developing countries have shown varying degrees of digital transformation, of which visually manifested in Fig. 2. In terms of digital infrastructure development and digital technology exploitation, the sample developing countries have displayed a trend of catching up with the sample developed countries. On the contrary, the digital trade volume of the sample developing countries is showing a steady state, while the proportion of digital trade of the sample developed countries gradually decreases. The development of digital industry in developed economies started early, and the development of digital economy is relatively leading. In the past period of time, the main development centers of digital trade were developed countries and China. With the active layout of global e-commerce giants in developing countries, digital trade continued to spread from developed countries to developing countries (Shaikh et al. 2020).

**Empirical research**

**Cross-sectional dependence and unit root test**

The threshold regression model requires the variables in the model, especially the threshold ones, to be stationary. Therefore, prior to the empirical regression, it is necessary to examine the unit root of each panel data series. In terms of the occurrence time, the panel unit root test method can be categorized into two stages. The first-generation panel unit root test requires independent section, and the test results of the first-generation panel unit root test may not be reliable when there is section correlation. The second-generation panel unit root test assumes the spatial effect of section correlation and makes different specifications for the form of sectional correlation, which can consider the sectional heterogeneity and correlation at the same time. The results of cross-sectional dependence test indicate that there is no cross-sectional correlation. Thus, we choose the first-generation unit root test.

In view of the robustness of the test results, this paper employs the LLC (Levin et al. 2002) test of homogeneous panel unit root hypothesis and the Fisher test of heterogeneous panel unit root hypothesis to validate the stationarity of each variable. Through test, the original series are unstable, which have unit roots. After first-order difference, the specific test results are reported in Table 3. It can be seen that the series of each variable presents a stable trend at first lag order, and all of them show the stationarity at the significance level of 1%.

**Cointegration test**

It can be observed from Table 4 that the trace statistics and Max-Eigen statistics corresponding to the null hypothesis of at most one cointegration relationship are greater than their respective 5% critical values, demonstrating that the null hypothesis is not rejected. Therefore, there is a cointegration relationship among carbon emissions, per capita energy consumption, the proportion of renewable energy consumption, digital infrastructure development, digital trade competitiveness, digital technology exploitation, urbanization, patent applications, trade openness, and per capita GDP, and there is at most one.

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**Table 2** Descriptive statistics of the variables

| Type of variables       | Variable name          | Symbol | Mean   | Standard deviation | Min    | Max    | Skewness | Kurtosis |
|-------------------------|------------------------|--------|--------|--------------------|--------|--------|----------|----------|
| Dependent variable      | Carbon emission        | CE     | 7.8158 | 4.5041             | 0.8873 | 20.4719| 0.6509   | 2.9363   |
| Core independent variables | Energy consumption     | EC     | 2.1027 | 0.3648             | 0.9751 | 2.7984| −0.8593  | 3.3977   |
|                         | Renewable energy consumption | REN    | 15.4173| 14.2806            | 0.0066 | 57.9803| 1.1098   | 3.1878   |
| Threshold variables     | Digital infrastructure development | INRT  | 55.6368| 28.2311            | 0.5275 | 96.5  | −0.4568  | 1.9523   |
|                         | Digital trade competitiveness | ICT   | 10.1787| 11.0743            | 0.0015 | 54.9744| 1.5297   | 4.9733   |
|                         | Digital technology exploitation | PAP   | 4.3691 | 0.6274             | 2.3037 | 7.5675| −0.5769  | 3.7391   |
| Control variables       | Urbanization rate      | URB    | 71.7376| 17.6438            | 24.374 | 100   | −0.9104  | 3.2736   |
|                         | Patent application     | PAT    | 3.6951 | 0.9023             | 1.5314 | 6.1442| 0.5415   | 2.7785   |
|                         | Merchandise trade volume | TRD   | 1.8656 | 0.2691             | 1.2913 | 2.6408| 0.4207   | 3.0678   |
|                         | Per capita GDP         | GDP    | 4.2632 | 0.4909             | 2.8794 | 4.9465| −0.9296  | 2.9221   |
Fig. 2  Variation of digital transformation indices during the investigation period. a INRT. b ICT. c PAP
Estimation results of threshold effect

It can be seen from Table 5 and Fig. 3 that there is a single threshold for INRT at the significance level of 1%, and the threshold value is 1.8152. According to the processing method of panel data threshold regression model raised by Hansen (2000), taking 1.8152 as the tipping point, IDRT is divided into two intervals of no bigger than 1.8152 and greater than 1.8152, and the relationship between EC and carbon emission is regressed in different intervals to investigate the impact of INRT on energy-related carbon emission at varied scales. There is also a single threshold for PAP at the 10% significance level (Figs. 4 and 5). When EC and REN are considered endogenous explanatory variables, the thresholds are 3.9341 and 3.7697, respectively (Fig. 6). Similarly, the threshold of ICT is 4.1009 when considering REN as endogenous explanatory variable (Kourtellos et al. 2016), which is significant at the 10% level (Fig. 5).

The statistics of autocorrelation within-group and heteroscedasticity between-groups of variables are 53.427 and 3121.43, respectively, which reject the null hypothesis at the 1% significance level. That is, there exist autocorrelation within-group and heteroscedasticity between-groups among the variables. The statistic of cross-sectional dependence is 22.151, which does not reject the null hypothesis. Thus, there is no cross-sectional dependence among the variables. In the baseline regression analysis, this paper adopts the feasible generalized least squares estimation (FGLS) method, which can effectively overcome autocorrelation within-group and heteroscedasticity between-groups. The results are shown in column (1) of Table 6. The influence coefficients of energy consumption and renewable energy consumption on carbon emissions are significant at the 5% test level, with a sign of positive and negative. For panel threshold estimation, the regression results are consistent whether regressing with only EC or other control variables are added.

| Variable name | Form (c,t,l) | LLC test Statistic | LLC test Probability | Fisher test Statistic | Fisher test Probability |
|---------------|--------------|--------------------|----------------------|-----------------------|------------------------|
| CE            | (c,0,1)      | -2.6629            | 0.0000               | 107.9515              | 0.0000                 |
| EC            | (c,0,1)      | -4.3716            | 0.0000               | 138.5581              | 0.0000                 |
| REN           | (c,0,1)      | -1.1901            | 0.0000               | 114.2067              | 0.0000                 |
| INRT          | (c,0,1)      | -2.8639            | 0.0000               | 125.9601              | 0.0000                 |
| ICT           | (c,0,1)      | -34.2929           | 0.0000               | 207.1324              | 0.0000                 |
| PAP           | (c,0,1)      | -1.7616            | 0.0000               | 87.8944               | 0.0000                 |
| URB           | (c,0,1)      | -5.2491            | 0.0000               | 193.2073              | 0.0000                 |
| PAT           | (c,0,1)      | -2.2393            | 0.0000               | 165.4094              | 0.0000                 |
| TRD           | (c,0,1)      | -1.6841            | 0.0000               | 121.5471              | 0.0000                 |
| GDP           | (c,0,1)      | -3.5087            | 0.0000               | 115.3419              | 0.0000                 |

c,t,l denote test with constant term, time trend, and lag order, respectively.
We discuss the regression results by adding all variables. When INRT is less than or equal to 1.8152, the coefficient of EC is 0.9521, which means when energy consumption increases by one percentage point, carbon emissions will increase by 0.9521 percentage points. When INRT is greater than 1.8152, the coefficient of EC is 0.9398, which is also highly significant. This manifests that with the expansion of digital infrastructure scale, the promotion effect of energy combustion on carbon emission is gradually weakened. The development level of the Internet can affect the R&D process, transmission efficiency, absorption degree, and application effectiveness of a series of digital low-carbon technology services, thus affecting the enhancement of a country’s low-carbon technological standard (Liddle 2018;
Through the application of industrial Internet platform in resource allocation and optimization, it can organize and schedule the scattered and massive resources and improve the matching performance of production resources and total factor energy efficiency (Balsalobre-Lorente and Leitão, 2020; Yan et al. 2020). When PAP is selected as the threshold variable, the estimated coefficient of EC is 1.0461 when PAP is no bigger than 3.9341. Nevertheless, the coefficient descends to 1.0243 when the threshold is greater than 3.9341. It implies that after crossing a certain threshold of digital technology exploitation, the major exporting countries will be able to improve the utilization efficiency of energy resources and help achieve carbon emission abatement. The dynamic threshold (Caner and Hansen...
Threshold regression results with EC as the endogenous variable

| Explanatory variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|----------------------|-----|-----|-----|-----|-----|-----|-----|-----|
| EC                   | 0.5377*** | (0.0190) |       |       |       |       |       | 0.7506*** | (0.0391) |
| REN                  | −0.0065*** | (0.0002) |       |       |       |       |       |       |       |
| EC_0                 | 0.9146*** | (0.0184) | 0.9521*** | (0.0346) | 0.9511*** | (0.0201) | 1.0461*** | (0.0314) | 1.3195*** | (0.2353) | 1.5365*** | (0.3502) | 0.0191* |
| EC_1                 | 0.8991*** | (0.0185) | 0.9398*** | (0.0353) | 0.9312*** | (0.0196) | 1.0243*** | (0.0317) | −0.3661*** | (0.1694) | −0.9396*** | (1.9787) | 0.0213 |
| Tipping point        | INRT ≤ |       | INRT ≤ |       | INRT ≤ |       | INRT ≤ |       | INRT ≤ |       | INRT ≤ |       | INRT ≤ |
|                      | 1.8170 | 1.8152 | 4.0301 | 3.9341 | 1.7434 | 4.0239 | 1.8152 |       |       |       |       |       |       |
|                      | INRT > |       | INRT > |       | PAP > |       | PAP > |       | PAP > |       | PAP > |       | PAP > |
|                      | 1.8170 | 1.8152 | 4.0301 | 3.9341 | 1.7434 | 4.0239 | 1.8152 |       |       |       |       |       |       |
| URB                  | 0.0066 | (0.0684) | −0.0167 | (0.0823) |       | −0.0374 | (0.0816) | −0.1437 | 1.6045* | 0.2233*** |       |       |       |       |
| PAT                  | 0.0081 | (0.0054) | 0.0279*** | (0.0094) |       | 0.0422*** | (0.0096) | 0.0181 | 0.2502* | 0.0465*** |       |       |       |       |
| TRD                  | −0.0031 | (0.0096) | −0.0372** | (0.0207) |       | −0.0968*** | (0.0203) |       |       |       |       |       |       |       |
| GDP                  | 0.1267*** | (0.0293) | −0.1232*** | (0.0333) |       | −0.2056*** | (0.0301) | 0.1456** | 0.3357 | 0.0999*** |       |       |       |       |
| _cons                | −0.4503*** | (0.1176) | −1.1037*** | (0.0387) | −0.6632*** | (0.1138) | −1.1641*** | (0.0415) | −0.3886*** | (0.1068) | 0.6264 | −2.8388* | −1.7762*** |       |
| R squared            |       |       |       |       |       |       |       |       |       |       |       |       |       | 0.8595 |
| F-statistic          |       |       |       |       |       |       |       |       |       |       |       |       | 128.68 |
| Model                | Dynamic | Dynamic | FE |       |       |       |       |       |       |       |       |       |       |       |

*p < 0.1, **p < 0.05, ***p < 0.01. The values in the brackets are standard errors.

The carbon emission reduction effect of digital economy is mainly reflected in several respects. Digital industry has its own environment-friendly characteristics, which has little negative effect on the environment (Alola 2019; Wei et al. 2020). The digital industry is dominated by information enterprises such as Internet enterprises and information service industry, and its green level is generally higher than that of traditional manufacturing industry. Besides, digital enterprises often pay more attention to environmental benefits because of their strong economic preponderance (Fu and Zhang 2015; Kaya et al. 2017). As the industrial foundation of digital economy, digital industry can promote other sectors to reduce carbon emissions. Digital industry can use the penetration and diffusion of digital technology to transform traditional industries, promote the development of intelligent and green industries, amplify industrial added value, and diminish energy consumption and carbon emissions (Boamah et al. 2017; Wang and Zhang 2021). The expansion of digital economy is beneficial to the establishment of carbon market, so as to drastically mitigate carbon emissions and attain carbon neutrality.

When renewable energy consumption is regarded as an endogenous explanatory variable, ICT and PAP are significant at the 10% level in Table 7. The thresholds are 4.1009 and 3.7697, respectively. The whole sample is divided into two threshold ranges: countries with low digital trade competitiveness and countries with high digital trade competitiveness. From the absolute value, renewable energy consumption has a weak to strong effect on carbon neutrality when ICT is greater than 4.1009, the coefficient is −0.0115 and passes the significance test at the 1% level. Low level of digital trade competitiveness is not conducive to the full release of carbon emission reduction effect of renewable energy. When ICT is greater than 4.1009, the coefficient is −0.0268 and shows significance at 1% level. It can be inferred that when digital trade competitiveness is at a high standard, the emission reduction effect of renewable energy is more evident. In the context of countries around the world responding to sustainable development, the share of renewable energy consumption in several countries has been close to 40%. Hence, in the
The process of using renewable energy to replace fossil energy, countries should be fully aware of the role of emerging digital technologies and take advantage of digital transition that can uplift the technological frontier to help coordinate the relationship between energy consumption transformation and green economic growth. The countries with high level of digital transformation are also displayed in Table 8.

Among the sample exporting economies, there are great discrepancies between developed and developing countries in industrial structure, technical level, carbon emission reduction stage, and the maturity of digital economy. Thereby, the carbon emission effect of digital transition shows differential performance among countries with varied development levels. Although the utilization of Internet in many exporting countries is at an initial stage, enterprises begin to employ the Internet in production, management, and trading activities. The “Internet plus” changes in production and business mode for manufacturing enterprises and service enterprises are also beginning to germinate (Zhong et al. 2018; Leitão and Balogh 2020). Since then, the significant positive effect of Internet usage on total factor carbon productivity has emerged. The empirical findings of this research are also consistent with those former studies (Boutabba 2014; Wang et al. 2019a, b). With the rapid progress of Internet and “Internet plus” key technologies and equipment, as well as the gradual enhancement of infrastructure construction, the Internet has more direct and extensive influence on the way of production and operation. Business model innovation continues to grow, and machinery and equipment are upgraded. The application of digital transformation in production, R&D, management, and other activities is becoming

| Table 7 | Threshold regression results with REN as the endogenous variable |
|---------|---------------------------------------------------------------|
| Explanatory variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| REN_0 | −9.5656*** | −0.0115*** | −0.0133*** | −0.0086*** | 0.0039 | 0.0093 | 0.0347 |
| | (1.6994) | (0.0004) | (0.0004) | (0.0005) | (0.0048) | (0.0032) | (0.0228) |
| REN_1 | −0.0138 | −0.0100*** | −0.0038*** | −0.0119*** | −0.0144*** | −0.0129*** | −0.0561*** |
| | (0.0003) | (0.0004) | (0.0014) | (0.0004) | (0.0028) | (0.0056) | (0.0226) |
| Tipping point | ICT ≤ ICT ≤ PAP ≤ PAP ≤ ICT ≤ PAP ≤ ICT ≤ |
| | 0.0812 | 4.1009 | 5.4569 | 3.7697 | 18.6099 | 4.5587 | 9.0316 |
| ICT > ICT > PAP > PAP > ICT > ICT > |
| | 0.0812 | 4.1009 | 5.4569 | 3.7697 | 18.6099 | 4.5587 | 9.0316 |
| URB | 0.2717*** | 0.6257*** | 0.0153*** | −1.5186*** | 0.5068*** | |
| | (0.0916) | (0.1015) | (0.1775) | (0.9564) | (0.0004) | |
| PAT | 0.0659*** | 0.0525*** | −0.0601*** | −0.0776 | 0.0684*** | |
| | (0.0103) | (0.0102) | (0.0136) | (0.1192) | (0.0994) | |
| TRD | −0.0399** | −0.0242 | |
| | (0.0235) | (0.0230) | |
| GDP | 0.0768*** | 0.0561** | −0.0735 | 0.3021 | 0.3617*** | |
| | (0.0339) | (0.0337) | (0.0614) | (0.4121) | (0.0371) | |
| _cons | 1.0186*** | −0.0268*** | 1.0054*** | −0.5606*** | 0.2305 | 0.3251 | −1.8637*** |
| | (0.0063) | (0.1238) | (0.0063) | (0.1385) | (0.4315) | (1.1293) | (0.1819) |
| R squared | 0.5581 | 0.7101 | 0.5756 | 0.6993 | 0.8405 |
| F-statistic | 625.36 | 334.20 | 661.39 | 342.82 | 110.90 |
| Model | Dynamic | Dynamic | FE |

*p < 0.1. **p < 0.05. ***p < 0.01. The values in the brackets are standard errors

Table 8 Distribution of economies with high digital transition in 2019

High digital infrastructure development (INRT > 1.8152)

| Australia, Austria, Belgium, Brazil, Canada, France, Germany, Ireland, Italy, Japan, Malaysia, Mexico, Netherlands, Poland, Russia, Saudi Arabia, Singapore, South Korea, Spain, Sweden, Switzerland, Thailand, Turkey, UK, USA, Vietnam |

High digital trade competitiveness (ICT > 4.1009)

| Australia, Austria, Belgium, Brazil, Canada, France, India, Indonesia, Italy, Russia, Saudi Arabia, Spain, Switzerland, Turkey, UK |

High digital technology exploitation (PAP > 3.9341)

| Australia, Austria, Belgium, Brazil, Canada, China, France, Germany, India, Indonesia, Italy, Japan, Malaysia, Mexico, Netherlands, Poland, Russia, Saudi Arabia, Singapore, South Korea, Spain, Sweden, Switzerland, Thailand, Turkey, UK, USA |
increasingly popular. The role of digital transformation in strengthening total factor carbon productivity, energy conservation, and emission reduction is further enhanced (Arce et al. 2016; Tao et al. 2021).

**Test of robustness**

In order to ensure the robustness of the above empirical results, this paper divides the time span of the sample into the same two sub-periods to avoid the biased effect of time trend and makes regression in turn. Next, according to the characteristics of regional economic cooperation, it is divided into OECD countries and non-OECD countries. At the same time, we split the sample countries into Asia Pacific region, Europe region, and America region according to their geographical location characteristics. Finally, the explained variable is replaced by the carbon intensity per unit of GDP. The regression results in Table 9 reveal that when EC and REN are selected as different core explanatory variables, the carbon emissions reduction effect still occurs significantly after crossing the threshold of various indicators representing digital transformation.

**Conclusions and policy implications**

Based on the research perspectives of carbon neutrality and digital economy, this paper probes the influencing factors of carbon emissions in the world’s leading exporting economies. By selecting the panel data of 29 countries in the recent 20 years and constructing the panel threshold regression model, this paper empirically inspects the impact intensity of per capita energy consumption and the proportion of renewable energy consumption on the scale of carbon emission. From different dimensions of digital economy, the results demonstrate that when the three indicators representing digital transformation (digital infrastructure development, digital trade competitiveness, and digital technology utilization) cross each threshold value, the promoting effect of energy consumption on carbon emission decreases (Kunkel and Matthess 2020), while the enhancing effect of renewable energy on energy conservation and emission reduction increases significantly (Hu et al. 2018). In view of the research conclusions, this paper puts forward the following policy suggestions and development paths towards carbon neutrality for the major exporting nations:

**Table 9 Robustness check**

| Explanatory variable | 2000–2009 (1) | 2010–2019 (2) | OECD (3) | Non-OECD (4) | Asia and Pacific (5) | Europe (6) | Americas (7) | Carbon intensity (8) |
|----------------------|---------------|---------------|----------|--------------|---------------------|-----------|--------------|---------------------|
| EC_0                 | 0.5758***     | 1.2552***     | 0.5093***| 0.4731***    | 1.3017***           |           |              |                     |
|                      | (0.0671)      | (0.0329)      | (0.0825) | (0.0588)     | (0.0551)            |           |              |                     |
| EC_1                 | 0.5634***     | 1.2338***     | 0.4866***| 0.4552***    | 1.2962***           |           |              |                     |
|                      | (0.0677)      | (0.0327)      | (0.0818) | (0.0591)     | (0.0556)            |           |              |                     |
| REN_0                | -0.011***     | -0.0124***    |          |              |                     | -0.0157***| 0.0645        |                     |
|                      | (0.0066)      | (0.0006)      |          |              |                     | (0.0013)  | (0.0085)      |                     |
| REN_1                | -0.0124***    | -0.0124***    |          |              |                     | -0.0181***| -0.0096***    |                     |
|                      | (0.0066)      | (0.0006)      |          |              |                     | (0.0014)  | (0.0008)      |                     |
| Tipping point        | INRT ≤        | PAP ≤         | INRT ≤   | INRT ≤       | INRT ≤             | ICT ≤     | ICT ≤         |                     |
|                      | 1.7634        | 4.2870        | 2.4753   | 1.8367       | 1.8110             | 1.7389    | 1.6607        | 0.2912              |
|                      | (1.3070)      | (0.1971)      | (1.4444) | (1.1145)     | (1.1145)            |           |              |                     |
|                      | 1.7634        | 4.2870        | 2.4753   | 1.8367       | 1.8110             | 1.7389    | 1.6607        | 0.2912              |
|                      | (1.3070)      | (0.1971)      | (1.4444) | (1.1145)     | (1.1145)            |           |              |                     |
| URB                  | 0.3466***     | 0.1109        | 0.1679   | 0.4498***    | 0.5262             | 0.9364*** |              |                     |
|                      | (0.1307)      | (0.1971)      | (0.1444) | (0.1145)     | (0.8596)            | (0.1887)  |              |                     |
| PAT                  | 0.0371***     | -0.0141       | 0.0661***| 0.0627***    | -0.0597            | 0.0773*** |              |                     |
|                      | (0.0162)      | (0.0160)      | (0.0139) | (0.0122)     | (0.0425)            | (0.0211)  |              |                     |
| TRD                  | 0.0103        | -0.0092       | 0.0728***| 0.1126***    | 0.0386             | 0.0627    |              |                     |
|                      | (0.0283)      | (0.0351)      | (0.0437) | (0.0289)     | (0.0640)            | (0.0478)  |              |                     |
| GDP                  | 0.0808        | 0.1556***     | 0.1099** | 0.0347       | 0.0178             | -1.4571   |              |                     |
|                      | (0.0532)      | (0.0513)      | (0.0600) | (0.0567)     | (0.1162)            | (0.0708)  |              |                     |
| _cons                | -1.2132**     | 0.1903        | -1.8419***| -1.4175***   | -1.5762***         | -2.1001***| 2.2995**     | 4.5375***           |
|                      | (0.2038)      | (0.2561)      | (0.0726) | (0.2181)     | (0.1498)            | (0.4207)  | (1.2041)     | (0.2541)            |
| obs                  | 290           | 290           | 380      | 200          | 240                 | 260       | 80           | 580                 |
| R squared            | 0.8539        | 0.6477        | 0.5656   | 0.8432       | 0.8680             | 0.8664    | 0.2781       | 0.6464              |
| F-statistic          | 122.79        | 99.97         | 739.96   | 244.00       | 287.30             | 260.54    | 46.57        | 166.03              |

*p < 0.1. **p < 0.05. ***p < 0.01. The values in the brackets are standard errors.
(1) It is imperative to raise the scale of the application of renewable energy in digital infrastructure and minimize the effect of the usage of digital infrastructure on the climate. Encourage traditional industries to elevate energy efficiency through digitization, Internet of things, and new technologies. Driven by technology and mode innovation, promoting the construction of intelligent and low-carbon-oriented digital infrastructure to avoid high-carbon economic growth (Park et al. 2018). Foster the new mode of “Internet plus” technology innovation and development, and facilitate the realization of carbon neutrality targets. Promote the transformation of smart city governance; accelerate the coverage, penetration, and interconnection of smart sensors, smart devices, and communication platforms; realize advanced perception and high-precision intelligent control; promote efficiency reform and reduce the consumption of manufacturing resources; and eventually enhance the emission reduction effect of digital technology empowerment.

(2) Ameliorate the assessment system for the utilization of renewable energy in the digital industry. Strive to realize the deep integration of energy revolution and digital revolution, and further optimize the energy structure. In the aspect of energy consumption, it is necessary to comprehensively use digital technologies such as big data, cloud computing, and the Internet of things to change the mode of energy consumption and improve energy efficiency. It is suggested to associate the carbon neutrality target with the approval policy of the new data center and review the energy consumption condition of the new digital center project. Take the green zero carbon attribute of renewable energy power and its significance for achieving the goal of carbon neutrality into essential consideration (Kovacikova et al. 2021), comprehensively inspect total energy combustion volume and energy consumption structure, and coordinate the large-scale expansion of data center and green low-carbon transformation.

(3) Elevate the incentive mechanism for boosting the adoption of clean energy in the digital industry. Vigorously promote the novel concept of renewable energy consumption through the Internet; help traditional consumers in industries, services, and other industries change from “energy consumers” to new “energy producers and consumers”; and reduce the proportion of traditional energy consumption. Optimize the energy consumption structure and actively promote carbon emission reduction projects. Guide capital flows and give play to the low-carbon leveraging role of public investment. Gradually form the project construction standard, and establish the directory of low-carbon digital industry. Support new energy and carbon emission reduction through fiscal and monetary policies. Set up incentive funds to encourage digital industries and enterprises to purchase clean energy. Take advantage of the synergistic incentive effect of fiscal and tax subsidies and market mechanism (Lau et al. 2014). Furthermore, continue or strengthen the policy support for the usage of green power in the digital industry.

(4) Steadily advance the digital transition and refinement of industrial structure, stimulate the technology regeneration of traditional manufacturing industry, and accelerate the elimination of backward technology and production, so as to abate the environmental burden. Optimize the energy consumption structure, diminish the dependence on coal-based fossil energy, and meanwhile increase the exploitation and application of clean energy such as wind, hydro-power, and solar energy. Concentrate on attracting international advanced technology investment, particularly knowledge and technology intensive investment in the field of resources and environment. Strengthen environmental regulation and raise the environmental pollution compensation cost of enterprises (Dou et al. 2021), thus to expedite enterprises to consciously form a resource intensive and environment-friendly ecological production mode. Strengthen digital innovation R&D and improve technical support capacity. At the same time, focus on the research and development of low-carbon energy and carbon capture technology, catalyze technological innovation and emission reduction effect, and enlarge the support capacity of digital technology.

(5) High-income-developed economies should take the initiative to help low- and middle-income developing countries accelerate the development of low-carbon economy. Due to the first mover advantages, developed countries have successfully achieved carbon peak with the assistance of their leading international division of labor and international trade system. Developing countries are in the middle- and low-end and relatively passive position in the global value chain. At the current stage, it is difficult to balance growth and emission reduction (Fourcade and Kluttz 2020). While enjoying the dividends of structure sophistication and open economy, developed economies should actively undertake their obligations, take the initiative to aid developing countries speed up the construction of circular low-carbon production systems, and jointly promote global emission reduction by using existing funds and digital technologies. In the light of the endowment varieties of different countries and the impact of digital economy on carbon emissions, adjust the development pace of digital economy, break down the industrial barriers and international restrictions of new models and new
business forms, and promote the coordination of digital economy governance in various countries.

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Author contribution Huan Zhang: Conception, writing, data curation, proof reading, and editing.

Data availability The data used for this study is available in from WDI database of World Bank.

Declarations

Ethical approval This study does not involve ethical issues.

Consent to participate All the authors have consented their participation in this article.

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