The dynamic process mechanism of carbon reduction under the digital economy perspective

Jinfeng Guo[1, *, #], Zhiye Xu[2, #], Shumin Wu[3], Yiping Huang[4], Yiting Guo[5]

[1]Maynooth University International Engineering College, Fuzhou University, Fuzhou, China, 350108

[2]College of Computer and Data Science, Fuzhou University, Fuzhou, China, 350108

[3]School of Economics and Management, Fuzhou University, Fuzhou, China, 350108

[4]Newhuadu Business School, Minjiang University, Fuzhou, China, 350108

[5]College of Civil Engineering, Fuzhou University, Fuzhou, China, 350108

*Corresponding author: jinfeng.guo.2022@mumail.ie

[#]These authors contributed equally.

Abstract. In order to explore the dynamic influence mechanism of the carbon reduction from the perspective of digital economy, this paper measures the scale index of digital economy, carbon emission intensity and carbon emission efficiency based on the panel data of 30 provinces in China from 2013 to 2020. On this basis, a model is constructed to explore the impact of digital economy on carbon emission, which provides inspiration for the realization of the carbon reduction promoted by digital economy. It is concluded that the upgrading of industrial structure, the reduction of energy intensity and the improvement of technological innovation level are all the paths for the digital economy to promote the reduction of carbon emissions. Among them, the upgrading of industrial structure and the improvement of technological innovation level play a weak intermediary role, while the reduction of energy intensity plays a strong intermediary role. The impact of digital economy on carbon emissions has spatial spillover between adjacent regions. The significance of this paper is to give a complete measurement model of digital economy and carbon emission under the framework of inter-provincial and inter-annual. After considering the mediating effect of variable influence, the transmission mechanism and spatial spillover effect of digital economy on carbon emission are analyzed.

Keywords: digital economy, carbon emission intensity, carbon emission efficiency, spatial panel Durbin model.

1. Introduction

The problem of global climate change is becoming more and more serious. The international community is strengthening measures to deal with climate change. China has proposed a dual carbon goal, that is, to achieve ' carbon peak ' by 2030 and ' carbon neutrality ' by 2060. At present, China is in the stage of rapid development of digital economy. The application of digital technology can improve the efficiency of resource allocation in the whole economy and society, accelerate the promotion of green and low-carbon development, and tend to become the key to high-quality promotion of carbon reduction goals, which will help China achieve the carbon reduction goal as soon as possible.

Some scholars, such as Xie Yunfei(2022)[1], believe that the development of digital economy can significantly reduce **carbon** emission intensity, and there is a positive correlation between the two ; the spatial econometric model introduced by Miao et al.(2022)[2] and Li et al.(2022)[3] found that the digital economy has an inverted U-shaped and U-shaped relationship with local and neighboring carbon emissions, respectively. According to Zhou Yuanren and Chen Menggen (2023) [4], the current measurement methods of digital economy are mainly divided into accounting method and index method. Xu Xianchun and Zhang Meihui (2020) [5] adopted the accounting method. Many Chinese scholars have decomposed the Kaya formula and obtained the factors that have a significant

impact on China 's carbon emissions. At present, the mainstream methods for measuring carbon emissions are roughly divided into carbon emission coefficient method, life cycle assessment method and input-output method. Jiang Sanliang and Jia Fangfang (2023) [6] used the carbon emission coefficient method to measure urban carbon emissions.

Based on the panel data of 30 provinces in China from 2013 to 2020, this paper measures the scale index of digital economy, carbon emission intensity and carbon emission efficiency, and constructs benchmark regression model, mediating effect model and spatial panel Durbin model to explore the impact of digital economy on carbon emissions.

The marginal contributions of this paper are as follows: First, the research perspective is relatively new, which enriches the research on the environment of the digital economy and provides a complete measure from the digital economy to carbon emissions under the inter-annual and inter-provincial framework. Secondly, on the basis of considering that the variable factors affecting carbon emissions can indirectly affect carbon intensity and carbon efficiency by affecting intermediary variables, through spatial spillover effect test and interpretation analysis, grasping the characteristics of digital economy development in different regions is conducive to promoting the balanced development of regional green and low carbon. Studying the mechanism of digital economy on carbon emission reduction will provide theoretical reference and empirical support for the implementation of carbon emission reduction measures, the achievement of carbon reduction goals and the realization of green low-carbon transformation and development.

2. Research Design

2.1. Data

In this study, data from 30 provinces except Tibet were selected as samples. The original data were derived from the 2013-2020 ' China Statistical Yearbook ' issued by the National Bureau of Statistics.

Due to the lack of some data in 2013 and 2014, the data processing is carried out in advance, and the linear interpolation method and ARIMA model are used to fill the vacancy part. This study uses the threshold method to standardize the data.

2.2. Variable Description

2.2.1 Explained variables

Carbon emission intensity (cei) refers to carbon dioxide emissions per unit of GDP.

Carbon emission efficiency (cee) incorporates the level of industry productivity into the established carbon emission level to reflect the performance of carbon emissions.

2.2.2 Explanatory variables

The scale of digital economy: From a broad perspective, this study divides the scope of digital economy into three parts: ' information development ', ' Internet development ' and ' digital transaction development '. The selection of indicators is shown in Table 1.

2.2.3 Intermediary variables

Energy intensity (eef): The Kaya formula emphasizes the impact of energy consumption per unit of GDP, that is, energy intensity, on carbon emissions. In general, energy intensity is positively correlated with carbon emissions.

Technical level (tec): STIRPAT model believes that another major factor affecting carbon emissions is technical level. Carbon emissions may increase or decrease due to advances in technology, which can reduce carbon emissions by improving energy efficiency or increase carbon emissions by increasing the intensity of production. In order to reflect the investment of the region in scientific and technological activities, this study uses R & D investment to measure the technical level.

Industrial structure (ind): The secondary industry includes a large number of industries with high energy consumption and large carbon emissions. Compared with the primary industry and the tertiary

industry, its production often has extremely high requirements for energy consumption. Generally speaking, the proportion of the secondary industry is positively correlated with carbon emissions, so the proportion of the added value of the secondary industry to the added value of GDP is used to measure the industrial structure.

2.2.4 Control variables

This study refers to the research of Zhang Tengfei et al. (2016) [7], and selects the degree of affluence (alc), population size (pls), environmental constraints (env), urbanization rate (urb), and openness (FDI) as control variables in combination with the actual situation. The specific measurement indicators are shown in Table 1.

Table 1. Variable description

variable type	sign	implication	measurement index	unit
variable being explained	cei	carbon emission intensity	Energy consumption per unit of GDP	Ton of standard coal / ten thousand yuan
	cee	carbon emission efficiency	Measured by the super-effect SBM model	percentage
core explanatory variables	DEI	Digital economy scale	Digital economy scale index	percentage
control variable	alc	wealth	per capita income	Yuan / person
	pls	population size	population density	People / square kilometers
	env	environmental constraint	Urban green coverage rate of municipal district	percentage
	urb	urbanization rate	Proportion of urban population in total population	percentage
	FDI	foreign openness	Foreign direct investment as a share of GDP	percentage
mediator variable	ind	industrial structure	The proportion of the added value of the secondary industry in GDP	percentage
	eef	energy intensity	Energy consumption per unit of GDP	Ton of standard coal / ten thousand yuan
	tec	technical level	Proportion of R & D investment	percentage

3. Model Design

3.1. Measurement of the scale of digital economy

The digital economy index system selected in this study refers to the research of Liu et al. (2020) [8], and the final weight is obtained through the combination of entropy weight method and analytic hierarchy process.

3.1.1 Entropy weight method（EWM）

The subjective weight Ui of each index is obtained by EWM method.

First, we calculate the weight of the jth indicator for the ith region:

$$w_{ij} = \frac{r_{ij}}{\sum_{i=1}^{n} r_{ij}} \tag{1}$$

According to the concepts of self-information and entropy in information theory, each evaluation index can be calculated as follows:

$$E_j = -\ln(n)^{-1}\sum_{i=1}^{n} f_{ij}\ln(U_{ij}) \tag{2}$$

Based on information entropy, the weight of each evaluation index defined before is further calculated:

$$U_j = \frac{1-E_j}{n-\sum_j E_j} \tag{3}$$

3.1.2 Analytic hierarchy process（AHP）

The objective weight V_i of each index is obtained by AHP method.

First, at the same level, we construct a judgment matrix to analyze the importance of indicators. Among them, X_{ij} and X_{ji} represent different evaluation indicators, i, j = 1, 2, 3, … n, n represents the number of indicators at the same level.

$$\begin{cases} X_{ij} = 1 \\ X_{ji} = \dfrac{1}{X_{ij}} > 0 \end{cases} \tag{4}$$

In order to ensure the importance of the judgment matrix, consistency check is performed.

3.1.3 Combined weights

The comprehensive weights obtained by subjective and objective weights, Qi, m and n, are weight distribution systems:

$$Q_i = mU_i + nV_i \tag{5}$$

The difference between m and n should be equal to the difference between the subjective weight Ui and the objective weight V_i and the sum of m and n is 1:

$$\begin{cases} m+n=1 \\ d(U_i,V_i) = d(m,n) \end{cases} \tag{6}$$

$$d(U_i,V_i) = \left[\frac{1}{2}\sum_{\mathrm{i}=1}^{\mathrm{n}}(\mathrm{U_i},V_i)^2\right]^{\frac{1}{2}} \tag{7}$$

$$d(\mathrm{m},\mathrm{n}) = |\mathrm{m}-\mathrm{n}| \tag{8}$$

The values of m and n are obtained by solving the equation, and Ui and Vi are brought in to obtain the final weight Q_{ijk}:

Calculate the index score of the s criterion layer in the i region, q is the total number of indicators contained in the index layer:

$$T_{is} = \sum_{i=1}^{q} M_j\, n_{ij} \tag{9}$$

Calculate the comprehensive evaluation index of the i th region, r is the number of index layers:

$$Z_i = \sum_{s=1}^{r} T_{is} \tag{10}$$

The digital economy index of each year selected for each region is calculated. The specific influencing factors are restated in Table 2 below.

Table 2. Evaluation index system of digital economy index

major index	first grade indexes	weight	weight	weight	measurement index	weight	indicator units	index attribute
Digital economy index	Information development indicators	0.4142	It infrastructure	0.1657	Optical cable density	0.0635	%	positive direction
					Mobile phone base station density	0.0691	%	positive direction
					Proportion of informatization employees	0.0331	%	positive direction
			ict impact	0.2485	Total telecommunications business	0.0994	%	positive direction
					Total telecommunications business	0.1491	%	positive direction
	Internet Development indicators	0.2103	Fixed end mutual	0.0841	Internet Access Port Density	0.0841	%	positive direction
			Mobile terminal mutual	0.0210	mobile subscription	0.0210	%	positive direction
			Fixed end mutual	0.0631	Proportion of broadband Internet users	0.0631	%	positive direction
			Mobile terminal mutual	0.0421	Proportion of mobile internet user	0.0421	%	positive direction
	Digital trading	0.3755	Digital transaction basis	0.0939	Proportion of enterprise websites	0.0413	%	positive direction
					Proportion of computers used by enterprises	0.0150	%	positive direction
					Proportion of e-commerce	0.0376	%	positive direction
			Impact of digital trading	0.2816	E-commerce sales	0.1126	%	positive direction
					Online Retail Sales	0.1690	%	positive direction

3.2. Calculation of carbon emission intensity

The regional carbon emission intensity (cei) is obtained by dividing the total regional carbon dioxide emission (cde) by the regional GDP:

$$\text{cei} = \frac{\text{cde}}{\text{GDP}} \tag{11}$$

According to the method of IPCC ' National Greenhouse Gas Emission Inventory Guidelines ' 2006 edition [9], the total carbon dioxide emissions (cde) are calculated, where i is the province, t is the year, j is the energy category, C is the total carbon emissions, E is the energy consumption, and η is the carbon emission coefficient:

$$cde_{it} = \sum E_{ijt} \times \delta_j (i = 29; j = 1,2, \dots 9) \tag{12}$$

3.3. Calculation of carbon emission efficiency

Taking each province as a decision-making unit (DMU) each year, regional capital stock, unit employees at the end of the year, and total electricity consumption as inputs, regional GDP as expected output, and carbon dioxide emissions as undesired output, the carbon emission efficiency

(cee) is calculated using the super-efficiency SBM model based on slack data envelopment analysis (DEA):

$$\rho^* = min \frac{\frac{1}{q}\sum_{i=1}^{q}\frac{\overline{x_i}}{x_{i0}}}{\frac{1}{u_{1+}u_2}\left(\sum_{r=1}^{u_1}\frac{y_r^g}{y_{r_0}^g}+\sum_{r=1}^{u_2}\frac{y_l^b}{y_{l_0}^b}\right)} \tag{13}$$

$$s.t. = \bar{x} \geq \sum_{i=1,\neq 0}^{n} \varphi_i x_i, \bar{y}^g \leq \sum_{i=1,\neq 0}^{n} \varphi_i y_i^g \tag{14}$$

$$\bar{y}^b \geq \sum_{i=1,\neq 0}^{n} \varphi_i y_i^b, \bar{x} \geq x_0, \bar{y}^g \leq y_0^g, y^{-b} \geq y_0^b \tag{15}$$

$$\sum_{i=1,\neq 0}^{n} \varphi_i = 1, \bar{y}^g \geq 0, \varphi \geq 0 \tag{16}$$

3.4. Influence mechanism model

3.4.1 Baseline regression model

In order to verify the impact of digital economy development on carbon emission intensity and carbon emission efficiency, a benchmark regression model is established:

$$CE_{it} = \rho_0 + \rho_1 \ln DEI_{it} + \rho_2 \sum CV_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{17}$$

3.4.2 Mediating effect model

In order to study the mediating effect of digital economy development on carbon emission intensity and efficiency, a mediating effect model is established:

$$M_{it} = \alpha_0 + \alpha_1 \ln DEI_{it} + \alpha_2 \sum CV_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{18}$$

$$CE_{it} = \beta_0 + \beta_1 DEI_{it} + \beta_2 M_{it} + \beta_3 \sum CV_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{19}$$

3.4.3 patial panel Dubin model

According to Liu Huajun et al. (2021) [10], carbon emissions have strong spatial correlation, so the original model is extended to the spatial panel Dubin model:

$$CE_{it} = \gamma_0 + \delta\omega CE_{it} + \gamma_1 DEI_{it} + \eta_1 \omega DEI_{it} + \gamma_2 \sum CV_{it} + \eta_2 \omega \sum CV_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{20}$$

4. Empirical analysis

4.1. baseline regression

After the baseline regression of the impact on carbon emission intensity and carbon emission efficiency, the data of table 3 are obtained. The results show that the regression coefficient of the digital economy index to carbon emission intensity is negative, and the regression coefficient to carbon emission efficiency is positive. Both carbon emission intensity and carbon emission efficiency are significant at the level of 1 %, indicating that the digital economy can effectively reduce carbon emission intensity and improve carbon emission efficiency.

Table 3. Benchmark regression results

variable	Two-way fixed results	
	(1) cee	(2) cei
DEI	0.121 (0.118)	-0.490* (-1.977)
FDI	0.367 (0.174)	-0.690 (-1.345)
urb	-5.539* (-2.302)	2.771** (4.747)
env	-0.027 (-1.416)	-0.003 (-0.630)
pls	0.003 (0.834)	-0.000 (-0.026)
alc	-0.000 (-0.977)	0.000** (6.457)
R 2	-0.927	-5.324
R 2(within)	0.305	-1.033
sample size	240	240
inspection	F (6,197)=2.106,p=0.054	F (6,197)=8.740,p=0.000
constant term	Dependent variable : carbon emission efficiency5.920** (2.771)	Dependent variable : carbon emission intensity-1.544** (-2.981)

* p<0.05 ** p<0.01 The t value in parentheses

4.2. Analysis of transmission mechanism

By constructing an intermediary model and based on formulas (18) and (19), the results in table 4 show that the digital economy can promote the optimization of industrial structure, the improvement of technological level and the weakening of energy intensity. In addition, the coefficients of columns (2) and (3) are significantly negative and positive at the 1 % level, indicating that the development of digital economy has the most obvious effect on reducing regional energy intensity, thereby inhibiting carbon emission intensity and improving carbon emission efficiency.

Table 4. Mechanism test results

	eef (1)	cee (2)	cei (3)	Tec (4)	cee (5)	cei (6)	Ind (7)	cee (8)	cei (9)
constant term	1.868** (6.015)	0.478** (2.747)	-8.372** (-8.306)	-0.033** (-5.794)	0.511** (2.740)	-2.694 (-1.574)	0.274** (4.211)	0.624** (3.517)	-0.787 (-0.459)
alc	-0.000 (-0.617)	-0.000 (-0.006)	-0.000 (-0.200)	0.000** (2.878)	-0.000 (-0.098)	0.000 (0.142)	-0.000** (-5.389)	-0.000 (-1.033)	-0.000 (-0.126)
pls	-0.000 (-1.824)	0.000 (0.938)	-0.000* (-2.130)	0.000* (2.505)	0.000 (0.843)	-0.001* (-2.100)	0.000* (2.365)	0.000 (1.416)	-0.001** (-2.905)
env	-2.565** (-3.529)	0.032 (0.078)	10.632** (4.720)	0.060** (4.539)	-0.029 (-0.067)	4.004 (1.025)	0.468** (3.076)	0.281 (0.687)	-1.735 (-0.440)
urb	1.119** (2.701)	-0.193 (-0.829)	6.021** (4.737)	0.022** (2.847)	-0.214 (-0.905)	12.611** (5.804)	0.115 (1.327)	-0.131 (-0.574)	10.679** (4.823)
FDI	-11.089** (-7.328)	0.441 (0.519)	4.978 (0.982)	0.070* (2.540)	0.370 (0.430)	-38.381** (-4.855)	0.485 (1.533)	0.699 (0.834)	-44.929** (-5.551)
DEI	-1.322** (-3.394)	0.896** (4.104)	-2.611** (-2.168)	0.005 (0.696)	0.891** (4.071)	-8.043** (-4.004)	0.197* (2.421)	1.001** (4.611)	-8.881** (-4.233)
eef		0.033** (0.890)	-4.399** (22.240)						
tec					1.002* (0.497)	-77.312* (-4.181)			
ind								0.532* (-3.087)	-2.313* (1.388)
Year fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
sample size	240	240	240	240	240	240	240	240	240
R 2	0.463	0.269	0.775	0.744	0.27	0.343	0.266	0.298	0.3
adjustR 2	0.449	0.251	0.768	0.738	0.248	0.324	0.247	0.277	0.279

* p<0.05 ** p<0.01 The t value in parentheses

4.3. Spatial spillover effect

Acording to previous studies, there are obvious differences in the intensity and benefits of digital economy and carbon emissions in various regions, and its impact on carbon emissions needs to be analyzed. The geographical distance spatial weight matrix and the global Moran 's index are used to test the spatial correlation. Table 5 shows that from 2013 to 2020, the Moran 's index of the development level of digital economy and carbon emission intensity and efficiency is significantly greater than 0, indicating that there is a positive spatial autocorrelation.

Table 5. Moran index of carbon emission intensity and carbon emission efficiency

particular year	cei		cee		particular year	cei		Cee	
	Moran's I	z value	Moran's I	z value		Moran's I	z value	Moran's I	z value
2013	0.088	3.726	0.038	0.099	2017	0.075	3.324	0.022	1.723
2014	0.088	3.718	0.015	0.607	2018	0.074	3.306	0.02	1.646
2015	0.081	3.512	0.007	0.827	2019	0.068	3.124	0.053	2.654
2016	0.074	3.309	0.005	1.188	2020	0.058	2.83	0.023	1.74

Table 6 shows that there is a positive spatial spillover effect on carbon emission intensity and efficiency, and the local carbon emission intensity and carbon emission efficiency are affected by geographical location. When the digital economy suppresses local carbon emissions, it also suppresses neighboring areas and improves the carbon emission efficiency of local and neighboring areas, indicating that the digital economy has a positive spillover effect on carbon emission efficiency.

Table 6. Spatial spillover effect results

variable	cei			variable	Cee		
dei	-0.086***	direct effect	-0.149***	dei	0.093***	direct effect	0.099***
Wdei	-0.492***	indirect effect	-0.634***	Wdei	0.092***	indirect effect	0.186***
ρ	0.346***	gross effect	-0.784***	ρ	0.512***	gross effect	0.412***
control variable	Yes			control variable	Yes		
Year fixed	Yes			Year fixed	Yes		
City fixed	Yes			City fixed	Yes		
N	240			N	240		
R2	0.116			R2	0.116		

5. Robustness test

This study reduces the possibility of bias caused by the selection of dependent variables by replacing the explained variables and explanatory variables. The table 7 results show that the estimated coefficient of digital economy on per capita carbon emissions is negative, and the estimated coefficient of single factor carbon efficiency is positive, indicating that the benchmark estimation results are reliable. In addition, by calculating the proportion of the added value of the digital economy to the added value of the GDP, the obtained digital economy development index is consistent with the previous results, which further verifies the robustness of the model.

Table 7. Robustness test results

variable	Replace the explained variable		Replace explanatory variables	
	lnco2	cee2	cei	cee
dei	-0.128***	8.645***		
dei2			-1.369***	1.356***
constant term	5.987***	5.234**	0.603***	0.537***
control variable	Yes	Yes	Yes	Yes
Year fixed	Yes	Yes	Yes	Yes
City fixed	Yes	Yes	Yes	Yes
N	240	240	240	240
R2	0.576	0.203	0.315	0.348

6. Conclusions and Suggestions

Through the empirical test of the benchmark panel regression model, it is found that for every 1 percentage point increase in the digital economy, it can effectively reduce the carbon emission intensity by 0.157 percentage points and increase the carbon emission efficiency by 0.145 percentage points. Through the empirical test of the mediating effect model, it is found that the upgrading of industrial structure, the reduction of energy intensity and the improvement of technological innovation level are all the ways in which the digital economy affects carbon emissions. Through the empirical test of the spatial panel Durbin model, it is found that the impact of the digital economy on carbon emissions has spatial spillover, which is particularly evident in the eastern region.

In order to reduce carbon emission intensity and improve carbon emission efficiency, there are the following suggestions: First, China should seize the opportunity of digital technology development, optimize industrial structure, reduce energy intensity, and improve the level of technological innovation, so as to achieve emission reduction. Second, China should formulate appropriate digital economy development strategies to promote the narrowing of the digital development gap among regions, so as to improve the level of environmental protection.

References

[1] Xie Yunfei.Effects and mechanism of digital economy on regional carbon emission intensity [J]. Contemporary economic management, 2022,44 (2): 68-78.

[2] Miao Lujun, Chen Jing, Fan Tianzheng, et al. The impact of digital economy development on carbon emissions-based on panel data analysis of 278 prefecture-level cities [J]. Southern Finance, 2022 (2): 45-57.

[3] Li Zhiguo, Wang Jie. How does the development of digital economy affect spatial carbon emissions under the background of economic agglomeration? [J]. Journal of Xi 'an Jiaotong University (Social Science Edition), 2022,42 (5): 87-97.

[4] Zhou Yuanren, Chen Menggen.Theoretical thinking and practical evaluation of digital economy measurement [J]. China Social Science Evaluation, 2023, No.33 (01): 73-84 + 159.

[5] Xu Xianchun, Zhang Meihui.Research on the scale measurement of China 's digital economy from the perspective of international comparison [J]. China 's industrial economy, 2020 (05): 23-41.

[6] Jiang Sanliang, Jia Fangfang. How does the digital economy promote carbon emission reduction Based on the study of urban carbon emission intensity and carbon emission efficiency [J]. Research World, 2023 (01): 14-21.

[7] Zhang Tengfei, Yang Jun, Sheng Pengfei.Effects and channels of urbanization on carbon emissions in China [J]. China 's population, resources and environment, 2016,26 (2): 47-57.

[8] Liu Jun, Yang Yuanjun, Zhang Sanfeng. Research on the Measurement and Driving Factors of China 's Digital Economy [J]. Shanghai Economic Research, 2020 (06): 81-96

[9] IPCC. 2006 IPCC Guidelines for national greenhouse gas inventories[R]. Intergovernmental Panel on Climate Change, 2006.

[10] Liu Huajun, Shao Mingji, Ji Yuanmeng. Dynamic evolution of spatial pattern and distribution of carbon emissions in China - An empirical study based on county-level carbon emission data [J]. Geographic Sciences, 2021,41 (11): 1917-1924.