Pol. J. Environ. Stud. Vol. XX, No. X (XXXX), 1-15

DOI: *10.15244/pjoes/197056* ONLINE PUBLICATION DATE:

Original Research

Study on the Impact of Digitalization and the Energy Consumption Structure on the Green Development of Sports Industry in China

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Received: 09 August 2024
Accepted: 08 December 2024

Abstract

The development of the sports industry, especially the green sports industry, under the low-carbon economy is of great significance to realizing a carbon neutrality goal. This study selects the data from 2008-2022 to verify the influence effect of digital development and energy consumption structure on the green development of sports industry (GDSI) and concludes as follows: (1) The GDSI has significant spatial autocorrelation, and with the change of time, spatial autocorrelation rises. (2) Digital development can promote the GDSI, and there is a spatial spillover effect. The energy consumption structure inhibits the improvement of the GDSI, and there is also a spatial spillover effect. The digital economy not only promotes the local GDSI but also has a significant effect on the GDSI in other regions; the direct, indirect, and total effects of the energy consumption structure are all significantly negative and pass the test of significance, which means coal consumption not only inhibits the local GDSI but also has a spatial spillover effect. (3) Digital development promotes the GDSI by improving the energy consumption structure, and 7.69% of the effect is realized by improving the energy consumption structure.

Keywords: digitalization, energy consumption structure, green development, sports industry

Introduction

Although the sports industry is considered a low-carbon industry in the beginning, with a series of innovations in the national system and the continuous progress of low-carbon technology in other industries, if it wants to feature in the advantageous ranks of a low-carbon industry, there needs to be innovation, improvement, and renewal in all aspects, whether the technology, the systems, or the concepts need updating [1-2]. China's sports industry is a comprehensive industry spanning the secondary and tertiary industries of the national economy, and scholars often raise problems regarding the unbalanced development of the industrial structure [3-4]. In addition, information technology, capital, intelligence, and talents in the sports industry are still relatively small [5-7]. Therefore, upgrading the green construction standards of stadiums

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can better meet the needs of national development, human development, and environmental development. This means that the green and low-carbon sports industry needs to carry out green environmental protection, high efficiency, and low energy consumption throughout the whole industrial chain, and it is more important to insist on green development in the growth process of the sports industry.

The digital economy, propelled by advancements in digital technology, has emerged as a pivotal force in shaping the future economic landscape [8-9]. This new paradigm integrates cutting-edge technologies like 5G, the Internet of Things (IoT), artificial intelligence (AI), cloud computing, and blockchain into the fabric of human production and daily life, rapidly reshaping the global allocation of resources, industrial composition, and competitive dynamics. In the realm of sports, which is both a source of joy and a vital component of community welfare, the industry stands as a burgeoning sector within the national economy. It fulfills the escalating aspirations of the populace for an enhanced quality of life. The "Outline for the Construction of a Strong Sporting Nation," released in 2019, underscores the importance of establishing a contemporary industrial framework. It advocates for the swift amalgamation of the Internet, big data, AI, and the tangible economy of sports. This integration aims to foster innovation in production, service delivery, and business models, thereby driving the evolution and advancement of the sports manufacturing sector and elevating the caliber and productivity of the sports service sector. The digital economy is an important driving force in promoting the GDSI and an important way to optimize China's economic and industrial structure [10]. This paper intends to take the current environment as an entry point and analyze the digital economy's connotation, power, and mechanism to drive the GDSI and put forward specific measures to promote the GDSI.

In the recent past, the principle of sustainable development, as endorsed by the nation, has steered the "low-carbon economy" into mainstream society [11]. The core objective of this movement is the efficient use of energy resources, particularly the reduction of reliance on carbon-intensive sources like coal and oil. This is achieved through a multifaceted approach that includes technological advancements, innovative systems, industrial restructuring, and the development of alternative energy sources. The goal is to curb the emission of greenhouse gases and to strike a balance between the pursuit of economic progress and the preservation of the ecological environment. The strategy aims to optimize energy usage by leveraging innovation in technology and systems, transforming industries, and fostering the growth of renewable energy sources. By doing so, it seeks to lessen the dependence on traditional high-carbon energy, thereby reducing the environmental impact. Energy, being the fundamental pillar of societal production, daily life, and the broader development of society, also holds a strategic position in the economic security of a nation. It is crucial for the sustainable and secure functioning of the economy.

The sporting goods manufacturing industry belongs to the secondary industry, and its national economic growth and its impact on social and economic development cannot be ignored. The sporting goods manufacturing industry mainly includes 5 categories: ball manufacturing, training and fitness equipment manufacturing, sports protective gear manufacturing, and sports equipment and accessories manufacturing, alongside other sporting goods manufacturing industries. Since the production and processing of sporting goods is the main goal, inevitably, energy consumption needs to be considered [12]. This raises the question of whether energy consumption in the GDSI is in a neutral position and whether the structural adjustment of energy consumption has a promoting effect on the GDSI. The research has theoretical value for formulating scientific and reasonable macroeconomic policies and realizing sustainable socio-economic development.

Based on this, this paper verifies the influence effect of digital development and the energy consumption structure on the GDSI and puts forward the corresponding suggestions, expecting to promote it.

Literature Review

Research on the GDSI

Under the influence of the "double carbon" goal, the sports industry needs to change the traditional crude development mode, accelerate the development of green sports manufacturing, build a green sports manufacturing system, and enhance the new growth point of sports manufacturing. Many scholars put forward different views on the definition of connotation, but generally, they are based on sustainable development goals. Some scholars believe that the GDSI is embodied in the low energy consumption and non-pollution adopted in producing sports [13-14], and some scholars explore the GDSI from the perspective of high-quality development. For example, Wang et al. [15] believe that realizing the green development of sports through GDSI implies that the sports industry, in the process of high-quality development, will need to make full use of technological innovation to continuously reduce energy consumption. There are also some scholars who put forward the concept of the GDSI from the perspective of ecological environmental protection and believe that the GDSI will help protect the ecological environment and reduce the consumption of resources [16-17]. Most scholars define the concept more consistently, aiming to achieve the goals of the sports industry along with environmental coordination for common sustainable development, which provides many references for this study. This paper is based on this discussion.

Research on the Digital Economy's Impact on the GDSI

Existing research is generally summarized in three areas: From the point of view of research mechanisms, the digital economy empowers the GDSI by optimizing industrial structure and perfecting factor allocation, etc.

The first aim is to study the mechanism of the digital economy. Most scholars study its direct effect, which can directly improve the total factor productivity of the sports industry and thus enhance the level of greening; for example, Ren and Huang [18], Shen et al. [19], Lou and Chen [20], and Bai and Yang [21] believe that the digital economy can improve total factor productivity and thus enhance the level of greening, mainly through the permeability, substitutability, and synergistic nature of digital technology. Some scholars study its indirect role, such as Ye [22], who argues that the digital economy indirectly acts on other factors of production to drive the GDSI.

Secondly, from the point of view of the elements of the study, the sporting goods manufacturing sector has the potential to evolve from a traditional manufacturing model to one characterized by "smart manufacturing." This transformation can be catalyzed by the rapid advancement of digital technologies [23], which enable the phasing out of obsolete production methods. It also involves refining energy consumption patterns and implementing strategies for carbon emission reduction through scientific and technological innovation. By integrating innovative scientific and technological solutions, the industry can enhance the sophistication of urban economies and the level of urbanization. These efforts contribute to optimizing the industrial structure, which minimizes resource wastage and enhances the efficient allocation of resources [24]. The goal is to lower the transaction costs for entities engaged in innovation, invigorate regional innovation dynamics, and expand the reach of digital technology. This comprehensive approach not only boosts the operational efficiency and quality of sporting goods manufacturing enterprises but also promotes green development practices. Integrating digital technologies and scientific innovations paves the way for a more sustainable and competitive industry better equipped to meet the evolving demands of the market and the environment [25-27].

Third, in terms of research methodology, after reviewing the relevant literature, more scholars use spatial spillover, VAR, and other models or theories based on TPB, impulse response function, and other theories to quantitatively or qualitatively analyze data [28-30].

Research on the Impact of the Energy Consumption Structure on the GDSI

Through a literature search, it is found that no scholars have discussed the relationship between the energy consumption structure and the GDSI, which is an important research value of this study. Existing studies mainly focus on the impact of energy consumption structure on regional green development. Most of the scholars' studies believe that improving energy structure and increasing renewable energy can promote the green development of the industry, such as Wang and Li [31]. Khan et al. [32] showed that renewable energy promotes economic development and the enhancement of green technology positive feedback on renewable energy consumption when renewable energy consumption and economic development are considered. Some scholars also discuss green development from the aspect of environmental quality; for example, Zafar et al. [33], Neagu, and Teodoru [34] found that renewable energy consumption can improve air quality. Some other scholars have discussed the mediating role of the energy consumption structure, such as Topcu [35] and Wang et al. [36], who found that energy consumption and green economic development are linear and play a part in the mediating effect between them, while the moderating effect is not significant.

In summary, many studies provide a reference to the research. However, the existing research still needs further expansion, mainly in the following aspects: (1) The relationship between the digital economy and the GDSI, where the past is mainly focused on direct and indirect roles; where the object of the research is mainly based on the region or the industry within the region; where few scholars are interested in its spatial spillover effect. Scholars have studied the spatial spillover effect, so this paper is based on the method of spatial measurement to carry out research to supplement and improve existing research. (2) Missing information, where the relationship between energy consumption structure and the GDSI has not been found in the literature. This paper examines the impact of the structure of energy consumption on GDSI, which can provide important theoretical references to green development and be a reference for the development of relevant policies. It can also provide references for relevant policy making.

Methodology

Model Construction

Super-Efficient SBM Model

Taking the panel data of 30 regions in China from 2008-2022 as samples, this paper constructs the evaluation index system of GDSI through input-output. It measures the GDSI based on the super-efficient SBM model.

The input of capital, labor, energy, etc. When producing the desired products and bringing the carbon emissions of non-desired output, the SBM model incorporates the non-desired output that is very practical, so it is widely used in measuring and analyzing eco-efficiency, total factor productivity, and green development efficiency. The SBM model not only considers the slackness of inputs and outputs but also deals with the defects of efficiency analysis brought by non-expected outputs. Therefore, based on the previous studies, the study adopts this model to measure GDSI.

In a hypothetical production framework comprising *n* autonomous decision-making entities, each is characterized by a set of inputs, desired and undesired. These entities utilize m distinct types of inputs to generate outputs. The input-output vectors can be delineated as follows:

Assuming a production system with n decision-making units, each consisting of inputs, desired outputs, and undesired outputs, m units of inputs are used to produce desired outputs and undesired outputs. The three input-output vectors can be expressed as follows: $x \in R^m$, $y^g \in R^{S_1}$, $y^b \in R^{S_2}$, X, y^g, y^b as follows:

$$X = [x_1, x_2, \cdots, x_n] \in R^{m \times n} \tag{1}$$

$$Y^g = [y_1^g, y_2^g, \cdots, y_n^g] \in R^{S_1 \times n} \tag{2}$$

$$Y^b = [y_1^b, y_2^b, \cdots, y_n^b] \in R^{S_2 \times n} \tag{3}$$

Assuming X> 0, $y^g > 0$, $y^b > 0$, the production possibility set can be defined as:

$$P = \{(x, y^g, y^b) | x \geq X\theta, y^g \geq Y^g\theta, y^b \leq Y^b\theta, \theta \geq 0\} \tag{4}$$

Where: θ represents a vector of weights; the evaluation decision unit (x_0, y_0^g, y_0^b) according to Tone's SBM model is:

$$\rho = min \frac{1 - \frac{1}{m}\sum_{i=1}^{m}\frac{S_i^-}{S_{i0}}}{1 + \frac{1}{S_1 + S_2}\left(\sum_{r=1}^{S_1}\frac{S_r^g}{y_{r0}^g} + \sum_{r=1}^{S_2}\frac{S_r^b}{y_{r0}^b}\right)},$$

$$s.t. \begin{cases} x_0 = X\theta + S^- \\ y_0^g = Y^g\theta - S^g \\ y_0^b = Y^b\theta - S^b \\ S^- \geq 0, S^g \geq 0, S^b \geq 0, \theta \geq 0 \end{cases} \tag{5}$$

Where: $S = (S^-, S^g, S^b)$ denotes the slack in inputs, desired outputs, and undesired outputs, ρ is the efficiency value, which ranges from 0-1. The above nonlinear model is transformed into a linear model through the Charnes-Cooper transform as follows:

$$\tau = mint - \frac{1}{m}\sum_{i=1}^{m}\frac{S_i^-}{x_{i0}},$$

$$s.t. \begin{cases} 1 = t + \frac{1}{S_1+S_2}\left(\sum_{r=1}^{S_1}\frac{S_r^g}{y_{r0}^g} + \sum_{r=1}^{S_2}\frac{S_r^b}{y_{r0}^b}\right) \\ x_0 t = X\mu + S^- \\ y_0^g t = Y^g\mu - S^g \\ y_0^b t = Y^b\mu - S^b \\ S^- \geq 0, S^g \geq 0, S^b \geq 0, \mu \geq 0, t > 0 \end{cases} \tag{6}$$

A common phenomenon in most efficiency evaluation studies is that multiple decision-making units have a 100 percent "state of efficiency." So, this paper chooses the super-efficient SBM model for measurement, and its model is as follows:

$$\rho^* = min \frac{\frac{1}{m}\sum_{i=1}^{m}\frac{\overline{x_i}}{x_{i0}}}{\frac{1}{S_1+S_2}\left(\sum_{r=1}^{S1}\frac{\overline{y_i^g}}{y_{r0}^g} + \sum_{r=1}^{S2}\frac{\overline{y_i^b}}{y_{r0}^b}\right)},$$

$$s.t. \begin{cases} \bar{x} \geq \sum_{j=1,\neq k}^{n}\theta_j x_j \\ \bar{y}^g \leq \sum_{j=1,\neq k}^{n}\theta_j y_j^g \\ \bar{y}^b \geq \sum_{j=1,\neq k}^{n}\theta_j y_j^b \\ \bar{x} \geq x_0, \theta \geq 0, \\ 0 \leq \bar{y}^g \leq y_0^g, \bar{y}^b \geq y_0^b \end{cases} \tag{7}$$

Where: ρ^* can be more than 1. In addition, $\bar{x}, \bar{y}^g, \bar{y}^b$ represents the target values of inputs, desired outputs, and non-desired outputs of the evaluated unit, and other variables are defined above.

Construction of the Input-Output Indicator System

In evaluating the GDSI, the core idea is to utilize lower inputs to bring higher desired outputs and lower non-desired outputs, better portraying the essential characteristics of green development. Table 1 provides specific indicators.

(1) Inputs

Labor input: In this research, the number of employees in the sports industry at the end of the year is used as a proxy variable for labor input.

Capital input: This paper adopts the perpetual inventory method for capital stock. The specific accounting process is shown in the following equation:

$$K_0 = \frac{I_0}{g_i + \delta} \tag{8}$$

$$K_{it} = K_{it-1}(1 - \delta) + I_{it} \tag{9}$$

Where: K_0 is the capital stock in the base period, I_0 is the real investment in the base period, and g_i is the real investment in 2008-2022. In the formula, K_{it} and K_{it-1} represent the value of region i in period t and period t-1, δ represents the capital depreciation rate and selects the capital depreciation rate of 10.96%, and I_{it} represents the actual investment amount of city i in period t. The gross fixed capital formation of the sports industry is chosen to represent the investment amount, and the fixed asset investment price index is used as the investment goods price index. In addition, considering the absence of a fixed asset investment price index for each region, this paper chooses a regional fixed asset investment price index to characterize it and uses this index to convert the nominal investment amount of each region to the real investment amount in the 2008 constant price.

Energy input: Energy is important in promoting industrial growth, and previous studies often use primary energy consumption as an energy input indicator. In this paper, the energy consumption of the sports industry is the topic of expression.

(2) Desired output

Select the sports industry's main business income and total profit of the sports industry to represent the desired output. The data of each region are calculated by the GDP index of corresponding provinces, with 2008 as the base period to eliminate the influence of inflation.

(3) Non-expected output

This paper uses industrial sulfur dioxide emissions, industrial smoke (dust) emissions, and industrial wastewater emissions as the three indicators of non-expected output.

Spatial Econometric Regression Models

Creation of the Spatial Weight Matrix

The correct and reasonable selection of a spatial weight matrix is crucial for spatial measurement. Different spatial matrices can lead to differences in the results. Currently, the spatial weight matrices are mainly the 0-1 spatial neighbor weight matrix, the spatial economic distance weight matrix, the economic and geographic nested weight matrix, and the spatial geographic distance weight matrix according to their composition.

There is no ready-made theoretical basis for the selection of matrices. In the study, two kinds of matrices are mainly used. One is the 0-1 spatial adjacency matrix (W1), where it depends on whether the regions are adjacent. If spatially adjacent, it is 1; if not spatially adjacent, it is 0, and the diagonal is all 0. The second one is the economic-geographical nested weight matrix (W2), expressed by using the inverse of the square of the geographic distance between the two regions and the product of the per capita GDP. The geographic distance between the two regions is calculated based on the latitude/longitude coordinate. The GDP of the two regions is the average GDP per capita between the two regions in the study year, and the diagonal is 0. The matrix is set up as follows.

(1) 0-1 adjacency matrix W1

$$W_{ij} = \begin{cases} 1, Region\ i\ is\ \ contiguous\ with\ region\ j \\ 0, Region\ i\ is\ not\ contiguous\ with\ region\ j \end{cases} \tag{10}$$

(2) Economic Geography Nested Weights Matrix W2

$$W_{ij} = \begin{cases} E_1E_2/d_{ij}^2\ i \neq\ j \\ 0, i = j \end{cases} \tag{11}$$

Where: d_{ij} denotes the geographic distance, E1 and E2 denote the per capita GDP.

Spatial Econometric Model Setting

Since the GDSI's spatial relevance cannot be ignored, the spatial econometric model is chosen to explore the spatial relationships. Spatial econometrics has gradually become the main content of econometrics. Spatial econometric models mainly include the spatial autoregressive model (SAR), the spatial error model (SEM), and the spatial Durbin model (SDM).

Table 1. System of input-output indicators.

Indicators	Indicator name	Specific indicators
Input indicators	Labor input	Number of people working in the sports industry
	Capital investment	Capital stock accounted for by the perpetual inventory method
	Energy inputs	Primary energy consumption
Output indicators	Expected outputs	Operating income of main sports industry units
		Total profit of the sporting goods manufacturing industry
	Non-expected outputs	SO2 Emissions/Main business revenue of industries above scale emission of soot and dust from above-scale industries/Main revenue solid waste emissions/Main revenue of industries above scale

SAR mainly examines whether changes in the explanatory variables of a certain region will have spillover effects on the surrounding neighboring regions. The specific formulas are as follows:

$$y_{it} = \alpha x_{it} + \rho w_{ij} y_{it} + \mu_{it} \tag{12}$$

Where: ρ is the coefficient of spatial autoregression, indicating the degree of influence of spatial elements on the explanatory variables.

SEM indicates that when the influence effect between regions is different due to differences in geographic location, the spatial dependence needs to be reflected with the help of the error term. The specific formula can be expressed as:

$$y_{it} = \alpha x_{it} + \mu_{it} \tag{13}$$

$$\mu_{it} = \lambda w_{ij} \mu_{it} + \varepsilon \tag{14}$$

Where: λ is the coefficient of the spatial error term, which represents the spillover effect of a change in a region's variable on neighboring regions, and ε is the error term.

The SDM model is applied in that the dependent variable in a region is affected by the independent variables in neighboring regions and the dependent variable in neighboring regions. The specific model is:

$$y_{it} = \alpha x_{it} + \rho w_{ij} y_{it} + \mu_{it} + \sigma w_{ij} x_{it} \tag{15}$$

Where: σ represents the effect of the explanatory variables in the neighboring areas' impact on the local explanatory variables.

Variable Selection

(1) Explained variables

GDSI: The data for this indicator is measured by the super-efficient model SBM introduced above.

(2) Explanatory variables

Digital development (DIG): This study draws on the indicator construction system and measurement method of Basal and Demircioglu [37], Tian, and Guo [38] and selects the objective entropy value method to assign weights to and measure the digital economy (dig) indicators. The indicators system is shown in Table 2.

Energy Consumption Structure (EC): The energy consumption structure reflects the diversity and dependence of a region or country on energy use and covers a wide range of energy types from fossil fuels (e.g., coal, oil, natural gas) to renewable energy sources (e.g., solar, wind, hydro, biomass). There are significant differences in the carbon footprints produced by the various energy sources after use, with the amount of carbon dioxide released from coal combustion being particularly prominent. According to energy consumption statistics, coal accounts for up to 60% of energy consumption in some regions. This data suggests that these regions may be highly dependent on coal resources, and the environmental impact of the combustion process of coal, as a high carbon emission energy source, cannot be ignored.

Table 2. Digital Development Indicator System.

Level 1 indicators	Level 2 indicators	Level 3 indicators	Indicator properties	Weights
Digital development	Digital infrastructure	Extent of long-distance fiber-optic cable routes	+	0.0772
		Internet broadband access subscribers	+	0.0653
		Number of pages	+	0.1004
		Mobile telephone exchange capacity	+	0.0965
	Digital technology applications	Number of new product development projects of industrial enterprises above designated size	+	0.0792
		Number of patent applications granted	+	0.0567
		Computers per 100 population	+	0.0671
		E-commerce sales	+	0.0854
	Digital industry development	Telecommunications revenue per capita	+	0.0612
		Mobile SMS traffic		0.0752
		Revenue from software operations	+	0.0812
		Total telecommunication services	+	0.0433
		Cell phone penetration rate		0.0611
		Number of employees in the information services industry	+	0.0502

Coal not only releases large amounts of carbon dioxide when burned but also causes serious damage to the environment during the mining process, including various problems such as air pollution, water pollution, and land degradation. Therefore, an in-depth understanding of the proportion of coal in the energy consumption structure of a region is crucial for assessing the level of green development in that region. To accurately assess the energy consumption structure of the sports industry, this study adopts the measurement method recommended by most scholars, i.e., characterizing coal consumption through its share of total energy consumption.

(3) Control variables

Gross domestic product (GDP): GDP promotes the adjustment and upgrading of industrial structure and has an important impact on GDSI. In the work, each province's regional GDP per capita is chosen as a control variable.

Urbanization level (UR): The increase in urbanization rate is beneficial to regional industries' development and resource pooling, which can maximize resource efficiency and fully demonstrate the scale advantage. However, at the initial stage, there are also some limitations, such as misallocation and mismatch of coordination. In this paper, the proportion of the urban resident population in the total resident population is chosen to characterize the situation.

Foreign Direct Investment (FDI): FDI can strengthen the international flow of production factors, stimulate production potential, improve resource flow efficiency, and realize industrial transformation and upgrading. In this paper, the level of openness is measured by the actual utilization of foreign direct investment as a percentage of regional GDP.

Industrial Development Level (IDI) is expressed as the percentage of industrial GDP to regional GDP. The level of regional industrial development affects the production capacity of sporting goods manufacturing enterprises, which in turn affects their carbon emissions and thus has an impact on the GDSI.

Based on the selection of variables, this paper produced the following descriptive statistics for each variable in Table 3.

Mediating Effects Model

The mediating effect reflects the influence of variable M in the path of independent variable X on dependent variable Y, and the mediating effect model is set up according to the above analysis. This research establishes a mediation effect model, which is as follows:

$$SG_{it} = \alpha_0 + \alpha_1 DIG_{it} + \alpha_2 GDP_{it} + \alpha_3 UR_{it} + \alpha_4 FDI_{it} + \alpha_5 IDI_{it} + \mu_{it} \tag{16}$$

$$EC_{it} = \beta_0 + \beta_1 DIG_{it} + \beta_2 GDP_{it} + \beta_3 UR_{it} + \beta_4 FDI_{it} + \beta_5 IDI_{it} + \varepsilon_{it} \tag{17}$$

$$SG_{it} = \gamma_0 + \gamma_1 DIG_{it} + \gamma_2 EC_{it} + \gamma_3 GDP_{it} + \gamma_4 UR_{it} + \gamma_5 FDI_{it} + \gamma_6 IDI_{it} + \sigma_{it} \tag{18}$$

Where α, β, and γ are the parameters to be estimated; μ, ε, and σ are, respectively, the random perturbation terms in the corresponding random perturbation terms of the model, and the specific testing procedure of the mediation effect model is:

In the first step, the significance of $\alpha 1$ was determined. If $\alpha 1$ is significant, the next step of the mediation effect test is conducted, and if $\alpha 1$ is not significant, further testing is not considered necessary. In the second step, the coefficients to be estimated, $\beta 1$ and $\gamma 2$, are tested, and if both are significant, the mediating effect is considered to exist, and the next test is carried out. If one of the two coefficients is not significant, the test goes directly to the fourth step, i.e., the Sobel test for the two coefficients. In the third step, according to the test results in the second step, if $\gamma 1$ is significant, it proves that there is a partial mediation effect; if $\gamma 1$ is not significant, it is considered that there is a complete mediation effect. In the fourth step, the Sobel test is conducted. If the test result is significant, it is considered that there is a mediation effect, but if the test result is not significant, it is considered that the mediation effect is not significant.

Table 3. Descriptive statistical results of variables.

Variable	Obs	Mean	Std.Dev.	Min	Max
GDSI	450	0.548	0.303	0.217	1.233
DIG	450	0.498	0.504	0.098	0.794
EC	450	0.666	0.722	0.328	0.804
GDP	450	11045	12214	8450	157279
UR	450	0.276	0.498	0.096	0.762
FDI	450	0.223	0.325	0.166	0.349
IDI	450	0.499	0.498	0.368	0.793

Results

Spatial Correlation Test

Before establishing the spatial measurement model for spatial measurement regression, it needs to test whether the GDSI has spatial autocorrelation, which is a necessary step for spatial measurement analysis. Only through the spatial autocorrelation test can we carry out further analysis. There are various methods to measure spatial autocorrelation, including Moran's I, Grtis's G, Geary's C, the semi-variance function, and the spatial autocorrelation coefficient diagram. In the study, we choose the more commonly used Moran's I index to conduct tests. The method is as follows:

$$Moran's\quad I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\,(x_i - \overline{x})(x_j - \overline{x})}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \tag{19}$$

$$S^2 = \frac{1}{\mathrm{n}}\sum_{i=1}^{n}(x_i - \overline{x})^2 \tag{20}$$

$$\overline{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{21}$$

In the above equation, n is the number of provinces, and x denotes the observation value of region i, respectively. To judge the spatial autocorrelation of spatial regions, we cannot only look at the value of Moran's I but first consider the results of the significance test. If the P-value is less than 0, then no matter whether the value is positive or negative, it is not a good sign. When the test is passed, if the value is greater than 0, it means positive relationships between them, but if Moran's I is less than 0, it indicates that the correlation between two variables is negative, and the spatial variability is stronger with the decrease of its value. When Moran's I = 0, it is considered that the spatial distribution of the variables is independent with no spatial correlation. Based on Stata 16.0 software, Moran's I of the GDSI value is shown in Table 4.

We can find that the GDSI is all greater than 0 and passes the significant test, meaning a significant positive spatial autocorrelation with a certain degree of spatial aggregation. Moran's I value of the GDSI basically shows an upward trend in the examination period. This indicates that with the change of time, the spatial dependence of the level of GDSI rises, and spatial autocorrelation rises through the continuous flow of production factors across regions.

Spatial Measurement Model Selection and Construction

After determining that the GDSI has significant spatial autocorrelation, it needs to screen the spatial measurement model. Reviewing the relevant literature shows that much of it does not carry out this step but directly chooses one model to study. The first step is to do the model test and select the appropriate model for the work. The specific steps in this paper are as follows:

First, the non-spatial model is estimated, and the Lagrange multiplier (LM) method is used to test the spatial lag and spatial error models. If the LM-lag test is satisfied and the LM-error passes and fails, the spatial lag model (SAR) is selected, and vice versa, the spatial error model (SEM) is selected. If both pass the test, the Robust LM-lag and Robust LM-error are further compared, and if the Robust LM-lag passes the test and the Robust LM-error fails, then the Spatial Lag Model (SAR) is selected, and conversely, the Spatial Error Model (SEM) is chosen. Second, suppose the non-spatial effects model is rejected. In this case, the Spatial Durbin Model (SDM) needs to be estimated according to the "General to Specific" to test whether it can be reduced to a spatial lag or spatial error model. Before estimation, the Hausman test is used to determine whether a fixed effects model is chosen, and then the likelihood ratio test

Table 4. Test values for Moran's I.

Year	GDSI		Year	GDSI	
	Moran	P-value		Moran	P-value
2008	0.2134	0.0000	2016	0.4324	0.0011
2009	0.2356	0.0000	2017	0.4513	0.0002
2010	0.2428	0.0000	2018	0.4789	0.0003
2011	0.2980	0.0000	2019	0.5013	0.0001
2012	0.3326	0.0000	2020	0.5214	0.0000
2013	0.3547	0.0001	2021	0.5423	0.0004
2014	0.3678	0.0000	2022	0.5567	0.0000
2015	0.3903	0.0000			

Table 5. Results of spatial econometric model tests.

Weighting matrix	Test Methods		Test value	P-value
W1	LM test	LM-lag	77.789	0.000
		LM-error	80.235	0.000
		Robust LM-lag	13.452	0.000
		Robust LM-error	25.567	0.000
	Hausman test	Hausman test	78.098	0.001
	LR test	LR test (ind or both)	54.346	0.002
		LR test (time or both)	543.892	0.000
		LR test SDM sar	66.732	0.002
		LR test SDM sem	72.124	0.000
	Wold test	Wold test SDM sar	15.643	0.023
		Wold test SDM sem	24.895	0.001
W2	LM test	LM-lag	90.421	0.000
		LM-error	134.432	0.000
		Robust LM-lag	6.457	0.000
		Robust LM-error	55.817	0.000
	Hausman test	Hausman test	26.342	0.069
	LR test	LR test (ind or both)	44.904	0.000
		LR test (time or both)	641.853	0.000
		LR test SDM sar	70.005	0.001
		LR test SDM sem	45.321	0.000
	Wold test	Wold test SDM sar	18.943	0.048
		Wold test SDM sem	29.005	0.000

(LR) is used to determine which fixed effects are used in the econometric model. Third, when estimating the spatial Durbin model, the Wald test or the LR test is used to verify whether the spatial Durbin model reduces to a spatial lag or spatial error model. If both tests point to a spatial lag or spatial error model, then the appropriate model can be chosen. If the LM test points to a model that is inconsistent with the Wald or LR test, then the spatial Durbin model is selected. According to the above steps, the models are tested in this paper, and the results are shown in Table 5.

Table 5 shows that selecting the spatial adjacency matrix W1, the LM test, and the robust LM test of spatial error and spatial lag rejects the original hypothesis, which indicates that the flow of production factors related to the GDSI has caused a certain impact on the level of neighboring GDSI and that the model has a certain amount of spatial interaction. Therefore, we cannot simply use mixed panel regression and initially select SDM for subsequent analysis. From the results of the LR test, it can be seen that the SDM cannot be degraded to the SEM and SLM under the adjacency matrix, and finally, we choose the SDM. The results of the Hausman test significantly show that the fixed effect model is better than the random effect model, and the results of the LR test show that the double fixed effect model cannot be degraded to the individual fixed effect model or the time fixed effect model, so it is better to choose the double fixed effect model. Combined with the results of the Wald test, it is further verified that it is more appropriate to use two-way fixed SDM to conduct studies.

If the economic-geographical nested weight matrix W2 is chosen, it can be seen from the test results that both LM-lag and LM-error are significant at the 1% level of significance. Meanwhile, Robust LM-error and Robust LM-lag both pass different significance levels, so the spatial Durbin model is still chosen at this point. Combined with the results of the Hausman test, the original hypothesis is rejected. After determining the use of a fixed effects model, the results of the LR test showed that the choice of an SDM with both individual and time fixed modes was preferable to either an individual fixed or a time fixed effects model, which further verified the appropriateness of using the SDM model in conjunction with the Wald test. Therefore, the

Table 6. Spatial effect regression results.

Variable	Two-way fixed effect
DIG	0.2246***(4.25)
EC	-0.3126***(-3.56)
GDP	0.0978**(2.02)
UR	-0.1451**(2.33)
FDI	-0.1121*(-1.91)
IDI	-0.2980***(-5.44)
W*DIG	0.1561***(3.48)
W*EC	-0.2256***(-5.21)
W*GDP	0.0532(1.01)
W*UR	-0.1344*(-1.89)
W*FDI	-0.0954**(-2.03)
W*IDI	-0.2398***(-4.15)
R2	0.9908
Log-likelihood	178.32
Hausman test	0.0000***(4.29)

Note: t-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1

SDM model with two-way fixed effects should be chosen to study, and the specific form is as follows:

$$SG_{jt} = \alpha + \rho WSG_{jt} + \beta_1 X_{jt} + \theta_1 WX_{jt} + \beta_j Z_{jt} + \theta_i WZ_{jt} + \mu_j + v_j + \varepsilon_{jt} \quad (22)$$

Where: β_1 and β_j denote the regression coefficients of the explanatory variables, θ_1, θ_i represents the spatial effect coefficients of the variables, X_{jt} is the explanatory variables, and Z_{jt} represents the control variables.

Spatial Effect Regression Results

W2 is chosen to conduct the model regression. The results are shown in Table 6.

Table 6 shows that the digital development coefficient is 0.2246, indicating that digital development can improve GDSI, which is consistent with the previous article. Meanwhile, the spatial regression coefficient is 0.1561, indicating that spatial effects are present. The energy consumption structure coefficient is -0.3126, indicating that the energy consumption structure can inhibit the GDSI, which is consistent with the previous article. Meanwhile, the spatial regression coefficient is -0.2256, indicating that t spatial effects are present. This paper utilizes partial differentiation to decompose the coefficient estimates of the explanatory variables into direct, indirect, and total effects.

Analysis of Spatial Spillover Effects

This paper utilizes partial differentiation to decompose the coefficient estimates of the explanatory variables into direct, indirect, and total effects. The decomposition result is as follows in Table 7.

Table 7 shows that the direct, indirect, and total effects of digital development on the GDSI are all significantly positive, indicating that the digital economy not only promotes the local GDSI but also promotes the GDSI in other regions. The reason for the direct effect and emergence of this result may be: First, digital technology can promote the digital transformation of the sports industry. The digital economy brings new industries, new modes, and new business forms, making the sports industry system more complex and diverse. Secondly, the digital economy is deeply integrated with the real economy. It permeates

Table 7. Decomposition results of spatial spillover effects.

Variable	Direct effect	Indirect effect	Aggregate effect
DIG	0.2413	0.1012	0.3425
EC	-0.2546	-0.1316	-0.3862

Table 8. Results of the mediation effect test.

Variable	Model 1 EC	Model 2 SG	Model 3 SG
DIG	-0.133***	0.289***	0.213***
EC			-0.167***
GDP	-0.098*	-0.176**	-0.185**
UR	-0.156***	-0.1156**	-0.134**
FDI	0.054*	-0.105*	-0.121*
IDI	-0.234***	-0.279***	-0.213***

Note: *** p<0.01, ** p<0.05, * p<0.1

all aspects of the production, operation, and sales of the sports industry, improving GDSI and promoting the transformation and upgrading of its structure. From the perspective of factors of production, data factors, as emerging factors of production, have a greater penetration effect on traditional factors of production such as labor and capital, improve the quality of traditional factors, enhance the efficiency of factor resource allocation, improve the benign interaction between factors, promote the concentration of factors to the advanced productive forces, and promote the GDSI. Thirdly, the digital economy has changed the demand structure of the sports market, and the change of demand structure has led to the adjustment of the sports industry structure and promoted the transformation and upgrading of the sports industry structure. The indirect effect mainly appears because of the inclusion of the digital economy, whose communication cost is basically zero, compresses the distance between time and space through efficient information transmission, and enhances the correlation of the sports industry among provinces. The convenience of access to raw material supply, market sales, and labor cost of the inter-provincial sports industry improves the resource utilization rate without lowering the development speed and development quality of the sports industry, which in turn reduces the carbon emissions of the sports industry. The digital economy's network virtuality can break geographic space limitations through data platforms and information technology, thus promoting the GDSI in the region and neighboring regions.

Table 7 also shows the relationship between the energy consumption structure and the GDSI; all effects are significantly negative, showing that coal consumption not only inhibits the GDSI but also has a significant inhibitory effect on the GDSI in other regions. Coal is a fossil fuel with high carbon content, and its combustion produces a large amount of carbon dioxide emissions. The coal combustion process releases atmospheric pollutants, including sulfur dioxide, nitrogen oxides, and particulate matter, which are the culprits of fine particulate matter PM2.5. When coal energy consumption accounts for a higher percentage, carbon emissions will rise accordingly, which will have an inhibiting effect on GFSI in the local region. The indirect effect indicates that the consumption of coal energy exacerbates the carbon emission level of neighboring regions because the industrial structure of neighboring regions tends to be similar, with a strong correlation and isomorphism of industries and a strong similarity in the energy consumption structure. The energy consumption structure of the native region may be transmitted to the neighboring regions, exacerbating the carbon emissions of the neighboring regions and thus inhibiting the green development of the industries in the neighboring regions.

Test of the Mediating Effect

This section constructs a mediating effect model to study the indirect impact of digital development on the GDSI by integrating digital development, an energy consumption structure, and the GDSI into the same framework. It empirically examines whether digital development can indirectly affect the GDSI through the energy consumption structure. Results are shown in Table 8.

In Table 8, model (2) shows that the influence coefficient of digital development on the GDSI is 0.289, which indicates that digital development has a significant role in promoting the GDSI. Model. (1) examines digital development's impact on energy consumption structure, and the impact coefficient is -0.133, showing that coal consumption decreases by 0.133% for every 1% increase in digital development. Model (3), compared with model (1), after adding the intermediary variable of the energy consumption structure, shows that the coefficient of digital development on the GDSI decreases from 0.289 to 0.213, which is due to the intermediary effect of the intermediary variable, and the intermediary effect is 0.022 (0.133*0.167). Digital development promotes the GDSI by improving the energy consumption structure. The coefficient of GDSI is 0.048, of which the mediating effect accounts for 7.69% (0.022/0.114) of the total effect, indicating that 7.69% of the effect of digital development on the GDSI is realized by improving the energy consumption structure. Digital development brings about the generation and proliferation of new

Table 9. Spatial effect regression results.

Variable	Two-way fixed effect
DIGt-1	0.1579***(3.77)
EC	-0.2568***(-4.44)
GDP	0.1124**(2.17)
UR	-0.1896***(3.99)
FDI	-0.1423*(-1.94)
IDI	-0.2568***(-4.79)

Note: t-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1

eco processes and technologies, eliminates backward industrial sectors, and promotes the integration of primary, secondary, and tertiary industries, which in turn improves energy utilization efficiency and upgrades the energy consumption structure. In short, upgrading the energy consumption structure can improve the GDSI. The above analysis shows that digital development promotes the GDSI by improving the energy consumption structure. After adding the intermediary effect, the model's mechanism has been improved, and it also provides ideas for the solution of real problems.

Robustness Testing

Endogeneity Test

Regions with a higher level of GDSI have a higher demand for digitization, thus stimulating the development of regional digitization. Therefore, theoretically, there may be reverse causality. Due to the difficulty of measuring digitization, this paper uses the lagged first-order digitization development index as an instrumental variable to regress again and test whether there is an endogeneity problem. The regression results are as follows in Table 9.

Heterogeneity Analysis

Due to China's vast territory and long history, there are significant differences in the level of economic development, resource endowment, industrial structure, and other aspects between different regions, and the impact of digital development on the GDSI will also show inter-regional differences. Therefore, this paper divides 30 provinces into east, central, and west groups for regression, and the results are as follows in Table 10.

Table 10 shows that for the eastern region, digital development can improve GDSI; for the western region, the impact of digital development on GDSI is not significant. The differences between different regions may be that the eastern region is more economically developed, the digital development started early, and the digital development market has formed a certain scale, which impacts the GDSI. The western region, however, has a late start in digital development, which is not enough to impact the GDSI. The energy consumption structure can reduce GDSI in all three regions; the difference is that the significance level is lower in the eastern region, and the significance and elasticity coefficient is the largest in the western region, indicating that the western region, which relies on the development of resources, has the largest negative impact.

Conclusions and Implications

Conclusion and Discussion

The main content of this paper is to study whether and how the digital economy and energy consumption structures affect GDSI. First, this paper combs through the relevant literature on the digital economy and energy consumption structure at home and abroad, and GDSI analyzes the influence paths based on the relevant literature, points out the possible spatial effects, and puts forward the corresponding hypotheses. Then, their relationships are empirically investigated by constructing a spatial econometric model, pointing out its spatial spillover, and carrying out robustness and heterogeneity tests.

Table 10. Heterogeneity analysis result.

Variable	Eastern	Central	Western
DIG	0.268***(3.38)	0.176***(2.97)	0.110(1.23)
EC	-0.098*(-1.88)	-0.2889***(-4.77)	-0.3890***(-3.18)
GDP	0.1654***(2.99)	0.1322**(2.13)	0.1745***(4.77)
UR	-0.0994(1.02)	-0.1890***(3.88)	-0.2109***(3.41)
FDI	0.0769*(1.93)	-0.1409***(-2.97)	-0.1908***(-5.66)
IDI	-0.1098*(-1.95)	-0.2652***(-3.57)	-0.3450***(-3.41)

Note: t-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1

The conclusions are as follows: According to the analysis of the spatial autocorrelation measure of GDSI, the study finds that GDSI has a significant spatial autocorrelation, and with the change of time, the spatial dependence of the level of GDSI rises through the continuous flow of production factors across the region; the spatial autocorrelation rises, which indicates that there is a positive spatial spillover effect between the GDSI of various regions. That is, sports industry development in one region will be driven by the green development of the sports industry in other regions, so starting from the spatial perspective and using the spatial measurement model to study the spatial effect in depth is necessary. This is consistent with the findings of most scholars.

According to the empirical results, it can be seen that: (1) The digital economy positively affects GDSI, but there is a significant negative impact relationship between the proportion of coal consumption and GDSI, which is consistent with the findings of previous scholars. (2) Considering the possible spatial spillover effect between the impacts, the analysis of the spatial econometric model concludes that digital development can indeed effectively promote the improvement of the level of GDSI, and there is a spatial spillover effect in the process of promoting the GDSI. The energy consumption structure inhibits the improvement of GDSI. At the same time, the spatial regression coefficient is negative and passes the significance test, indicating that there is a spatial spillover effect of the energy consumption structure in the process of influencing the GDSI. The direct, indirect, and total effects of digital development on the GDSI are all significantly positive and have passed the significance test, indicating that the digital economy not only promotes the local GDSI but also has a regional spatial spillover effect in the enhancement of its level of development and also has a significant effect on GDSI in other regions. The direct, indirect, and total effects of energy consumption structure are significantly negative; the large coal consumption not only inhibits the GDSI of the local sports industry but also has a significant inhibitory effect on the GDSI in other regions. (3) Digital development promotes GDSI by improving the energy consumption structure. 7.69% of the effect is realized by improving the energy consumption structure, and digitalization can bring about the generation and proliferation of new eco-processes and technologies, improve energy use efficiency, and promote the upgrading of the energy consumption structure. The upgrading of the energy consumption structure will enhance GDSI, so it can be concluded that digitalization is the driving force for upgrading and adjusting the energy consumption structure, which plays a significant role.

Recommendations

(1) Strengthen the digital industry infrastructure of the sports industry. The government needs to increase investment, improve the digital industry infrastructure, and incentivize sports enterprises to actively integrate into the digitalization process with the government's guiding role. The government can play a coordinating role in the construction of platforms, promote the deepening of the digital transformation of enterprises through measures such as procurement services and the creation of digital demonstration platforms, and address the high costs faced in the digital transformation process. At the same time, the government can attract high-tech enterprises to establish long-term cooperation mechanisms with sporting goods manufacturers through financial support and other means so that the latter can take advantage of the former's technological advantages and professional talents to realize the "cloud services, data-driven, and intelligent" enterprise upgrading. In addition, enterprises should implement the strategy of "bringing in and going out", strengthen exchanges, learn from the international advanced level, and actively participate in the digital cooperation of the international sports industry.

(2) Concentrate on cultivating the core force of digital innovation to improve the development quality of the digital economy. The study points out that the high-level development of the digital economy is crucial for promoting the GDSI. The cornerstones of the development of the digital economy are the continuous progress of the new generation of information and communication technologies, the overall quality improvement of researchers, and the support of government policies. Therefore, we must continue to target China's high-quality development strategy, strengthen the in-depth application of 5G networks, data storage centers, blockchain, and other modern infrastructures in the sports industry, and optimize the digital service system in order to provide more powerful data support for the high-quality growth of the sports industry. The government should also support the digitalization process of the sports industry and the cultivation of related professionals at the policy level and stimulate fiscal policy support for emerging technologies in the sports field.

(3) Enhance technological innovation and become a pioneer in the digital transformation of the sports industry. Increase investment in the innovation of digital technology in the sports industry, especially in technology-intensive regions; increase the allocation of research and development personnel and technical equipment; increase the proportion of this field in the sports industry; and promote the transformation of the industry from traditional factors of production to digital production methods. At the same time, it needs to adjust and optimize the structure of the sports industry, take advantage of technological innovation, create an environment conducive to GDSI, abate the structural obstacles faced by the sports industry, and provide a clear development path for the digital economy to promote the GDSI through technological innovation.

(4) The growth of China's sports industry shows a positive correlation with energy consumption, and energy consumption has become a key factor driving its stable growth, providing the necessary material foundation for the industry. As the scale of the sporting goods manufacturing industry continues to expand, its total demand for energy is expected to maintain high growth in the long term. In order to ensure the rapid development and sustained growth of the sports industry, it needs to properly deal with the balance between industrial development and energy consumption (supply), not only to carry out an in-depth transformation of the traditional energy industry but also to actively develop new energy sources, enhance the scientific and technological level of the energy industry, solve the problem of sustainability of the energy industry, and resolutely avoid short-term behavior. In addition, by strengthening international energy cooperation, we should promote the development of energy supply from unitary to diversified and establish a corresponding strategic energy reserve system to ensure the long-term stable growth of GDSI.

Limitations

The characteristics of different regions are different; this paper is limited to data availability and does not focus on smaller regions to start the discussion, which is also the main direction of this paper's future research.

Certain problems may exist in measuring variable indicators; this paper refers to many scholars who measure the specific indicators used in the study of the measurement method. Even so, there may be certain scientific problems that need to be further improved and supplemented in future studies.

Relevant recommendations can only be made based on empirical analysis when exploring policy recommendations. Due to the different characteristics of different regions, policy applicability may be problematic. Whether the policy is suitable for the specific region needs further examination, and this paper's future research needs to be further improved.

Conflict of Interest

The authors declare no conflict of interest.

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