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Factors Influencing Carbon Emission and Low-Carbon Development Levels in Shandong Province: Method Analysis Based on Improved Random Forest Partial Least Squares Structural Equation Model and Entropy Weight Method

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Abstract: Comprehensively clarifying the influencing factors of carbon emissions is crucial to realizing carbon emission reduction targets in China. To address this issue, this paper develops a four-level carbon emission influencing factor system from six perspectives: population, economy, energy, water resources, main pollutants, and afforestation. To analyze how these factors affect carbon emissions, we propose an improved partial least squares structural equation model (PLS-SEM) based on a random forest (RF), named RF-PLS-SEM. In addition, the entropy weight method (EWM) is employed to evaluate the low-carbon development level according to the results of the RF-PLS-SEM. This paper takes Shandong Province as an example for empirical analysis. The results demonstrate that the improved model significantly improves accuracy from 0.8141 to 0.9220. Moreover, water resources and afforestation have relatively small impacts on carbon emissions. Primary and tertiary industries are negative influencing factors that inhibit the growth of carbon emissions, whereas total energy consumption, the volume of wastewater discharged and of common industrial solid waste are positive and direct influencing factors, and population density is indirect. In particular, this paper explores the important role of fisheries in reducing carbon emissions and discusses the relationship between population aging and carbon emissions. In terms of the level of low-carbon development, the assessment system of carbon emission is constructed from four dimensions, namely, population, economy, energy, and main pollutants, showing weak, basic, and sustainable stages of low-carbon development during the 1997–2012, 2013–2020, and 2021–2022 periods, respectively.

Keywords: carbon emission; influencing factors; RF-PLS-SEM; EWM; low-carbon development level

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1. Introduction

According to the United Nations Intergovernmental Panel on Climate Change (IPCC), human social and economic activities have accelerated global warming, resulting in higher temperatures, rising sea levels, reduced biodiversity, and more frequent extreme climate events [1,2]. As a major contributor to global warming, CO_2 accounts for approximately two-thirds of global greenhouse gas (GHG) emissions [3]. The concentration of carbon dioxide in the atmosphere has increased from approximately 280 ppm in preindustrial times to 407.8 ppm in 2018 [4], and reached 420 ppm in 2021 [5]. Without adopting any effective action, the world's average temperature could rise by 1.4–5.8 degrees centigrade over the next 100 years, posing a major threat to global sustainable development [6]. Therefore, the continued increase in carbon emissions has become a global concern. Many countries have adopted mitigation strategies to reduce carbon emissions, including financial incentives or tax subsidies, support funds, insurance premiums, and noneconomic incentives such as regulations, standards, and bans [7]. It is essential for developing countries to improve their carbon reduction efficiency, which was proposed by the Paris Agreement [8].

China is the largest carbon emitter in the world, accounting for nearly 30% of global carbon emissions; thus, China has an obligation to play the leading role in reducing carbon emissions [9]. Moreover, China has pledged to peak its carbon dioxide emissions by approximately 2030 and is striving to achieve carbon neutrality by 2060. Hence, exploring scientific and comprehensive carbon reduction mechanism measures is urgently needed in China.

Since China's provinces differ greatly in terms of population, economy, industry, etc., it is important to study carbon emission reduction according to the actual situation of China's regions [10]. The carbon emissions of 34 provinces in China in 2021 are shown in Figure 1.

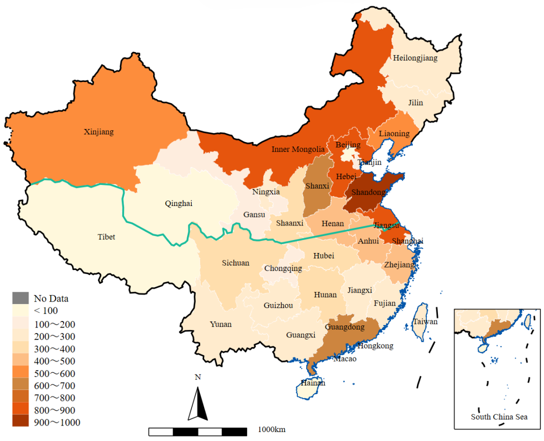

Figure 1. Carbon emissions of 34 provinces in China in 2021. Source of data: the carbon emission data for 30 provinces in China (excluding Hong Kong, Macao, Taiwan, and Tibet Autonomous Region) in 2021 were obtained from the China Emission Accounts and Datasets (CEADs), and the data for Hong Kong, Macao, Taiwan, and the Tibet Autonomous Region were obtained from the Environment and Ecology Bureau, the Environmental Protection Bureau of the Macao Special Administrative Region, the BIOSIS Previews database and the China Tibet News Network, respectively. The green line in the figure represents the Qinling-Huaihe River demarcation line, and the blue line, and the blue lines on the map represent islands or coastlines.

Figure 1 shows that the Shandong, Hebei, and Jiangsu Provinces and the Inner Mongolia Autonomous Region have the highest carbon emissions among all provinces and regions. Moreover, the Shandong and Jiangsu Provinces are the main sources of carbon emissions in eastern China, and Shandong Province ranks first in China, far exceeding other provinces and regions. In particular, Shandong is a developing province with high energy consumption and rapid urbanization. Owing to its heavy industry, the energy structure is biased toward coal, and many industries have high energy consumption and emissions; hence, research on the carbon peak and carbon neutrality in Shandong Province has attracted much attention. Moreover, establishing an influencing factor system for carbon emissions is crucial to investigate the development of low carbon emissions in Shandong Province.

2. Literature Review

Systematically identifying the influencing factors of carbon emissions and formulating effective strategies are critical to achieving the "30–60" dual-carbon target and realizing the goal of low-carbon sustainable development, such as economic growth, energy structure, and population distribution [11–13]. Considering the importance of ecological factors in influencing carbon emissions, He et al. [14] analyzed the relationship between water and energy from a life cycle perspective. In addition, Xian et al. [15] investigated the emissions of

SO_2, NO_X, CO, $PM_{2.5}$, and other pollutants via the multiresolution emission inventory model for climate (MEIC), concluding that the pollution abatement policy had a greater inhibitory effect on controlling air pollution and carbon emissions. In addition, trees absorb carbon dioxide through photosynthesis, and forests soak up carbon dioxide in the form of biomass and soil carbon. Teng et al. [16] introduced carbon sequestration by afforestation based on the relaxation measures to study the change in carbon emission efficiency in China. Their findings about utilizing natural ecosystems to sequester carbon and combat climate change are important. Cabon et al. [17] highlighted the importance of considering processes other than photosynthesis to estimate how much carbon trees can sequester, and their findings are important for utilizing natural ecosystems to sequester carbon and combating climate change.

Currently, the main models for studying the factors affecting carbon emissions include the input–output [18,19], Durbin [20–23], index decomposition analysis [24–26], panel threshold [27–29], and dynamic spatial econometric models [30]. However, these models do not systematically consider the influencing factors, and lack internal feedback.

The structural equation method (SEM), a popular method for exploring causal relationships, is applied to address barriers [31,32]. The SEM can extract all of the features of hidden information from the observed data while considering the structure and influence within the indicators, and can directly analyze the unmeasured attributes. In recent years, the SEM has played an important role in low-carbon research, such as low-carbon agriculture [33], travel [34], and building industries [35]. These studies are based on questionnaires or visiting survey methods. However, for the issue of carbon emissions, panel data have the advantage of the time dimension, which better reveals the changing patterns between carbon emissions and their influencing factors and avoids subjective judgments. For the first time, Wei et al. [36] utilized panel data and partial least squares structural equation modeling (PLS-SEM) to construct the path relationship between carbon emissions and their multiple influencing factors, assessing the degree of influence of each factor on different regions in China. They considered a two-level indicator system for carbon emission influencing factors and adopted traditional methods to eliminate observable variables with load values less than 0.7, achieving a goodness-of-fit (GOF) of 0.862 for the model. To comprehensively establish a carbon emission influencing factor indicator system and improve model fit, this paper constructs a four-level carbon emission influencing factor indicator system encompassing population, economy, energy, major pollutants, water resources, and afforestation. The random forest (RF) model is utilized to select variables highly correlated with carbon emissions, which are then combined with PLS-SEM, referred to as RF-PLS-SEM. The empirical analysis is conducted in Shandong Province, with the results indicating a significant improvement in the GOF of the refined model.

The innovations of this paper are as follows:

(a) This paper presents a four-level carbon emission influencing factor system, including six qualitative indicators, such as population, economy, energy, main pollutants, water resources, and afforestation, and 40 quantitative indicators, which is more comprehensive and systematic.

(b) Compared with traditional PLS-SEM, the improved RF-PLS-SEM substantially enhances the GOF from 0.8141 to 0.9220, and the loading exceeds 0.8. To reveal concealed information within the data, we investigate the mediating variables for the indirect influencing factors via RF-PLS-SEM. In particular, as a negative primary factor, the economic variable is quadratically decomposed via RF-PLS-SEM to explore which factors are important in inhibiting carbon emissions.

(c) Combining RF-PLS-SEM with the EWM, the carbon emission indicator system is used to calculate the low-carbon development score in Shandong Province. After feature selection and causal analysis by RF-PLS-SEM, the influencing factors are highly coupled in the low-carbon development evaluation model, and the direction of the indicators is determined according to the relationships between the data, to ensure high credibility of the evaluation results.

3. Data and Research Method

3.1. Data Source and Processing

In this study, we initially select the influencing factors that are highly related to carbon emissions from the six dimensions of economy, population, energy, water resources, major pollutants, and afforestation, which include six qualitative indicators and 40 quantitative indicators. The panel data are selected from Shandong Province from 1997 to 2022, and the information and sources of the variables are shown in Table 1.

Table 1. Basic data information.

Indicator (Variable Name)	Unit	Source	Literature
Carbon emissions (CE)	Mt CO_2	CEADs	[3,37–39]
Population (POP)			
total population (TP)	10,000 persons	Shandong Statistical Yearbook	[40]
density of population (DP)	person/sq·cm	Shandong Statistical Yearbook	[41]
Economic (ECO)			
per capita GDP (PCG)	yuan	Shandong Statistical Yearbook	[3]
gross domestic product (GDP) primary industry (PI) secondary industry (SI) tertiary industry (TI)	100 million yuan	Shandong Statistical Yearbook	[40,42]
agriculture, forestry, animal husbandry and fishery (AFAHF) industry (IND) construction (CON) wholesale and retail trade (WRT) hotels and catering services (HCS) transport storage and postal services (TSPS) financial intermediation (FI) real estate (RE)	100 million yuan	National Bureau of Statistics	[43]
Energy (ENE)			
total energy production (TEP) total consumption production (TCP)	10,000 tons of SCE	Shandong Statistical Yearbook; China Energy Statistical Yearbook	[44] [42]
fuel oil consumption (FOC) coal consumption (COAC) coke consumption (COKC) crude oil consumption (COC) kerosene consumption (KC) diesel oil consumption (DOC) gasoline consumption (GC)	10,000 tons	Shandong Statistical Yearbook; China Energy Statistical Yearbook	[42]
natural gas consumption (NGC)	10,000 million cu·m	Shandong Statistical Yearbook; China Energy Statistical Yearbook	[45]
electricity consumption (EC)	10,000 million kW·h	Shandong Statistical Yearbook; China Energy Statistical Yearbook	[46]
water resources (WR)			
water supply (WS) surface water resources (SWR) ground water resources (GWR)	10,000 million cu·m	Shandong Statistical Yearbook	[47,48]
total amount of water resources (TAWR)	10,000 million cu·m	China Water Resources Bulletin; Shandong Water Resources Bullet	[49]
Main pollutants (MP)			
volume of waste water discharged (VWW)	10,000 tons	Shandong Statistical Yearbook	[50]
volume of common industrial solid waste generated (VCISWG) volume of common industrial solid waste utilized (VCISWU) volume of sulfur dioxide discharged (VSDD) volume of particulate emissions (VPE)	10,000 tons	Shandong Statistical Yearbook	[15,51]
Afforestation (AFF)			
total area of afforestation (TAA) protection forests (PF) by-product forests (BF) fuel forests (FF) forests for special purpose (FSP)	hectare	China Forestry Statistical Yearbook	[52]

Note:The primary industry includes AFAHF; the secondary industry includes IND, CON; the tertiary industry includes WRT, HCS, TSPS, FI, RE.

3.2. Method

3.2.1. Random Forest (RF)

Feature selection by RF is important in building a classification system; it not only filters out important indicators but also reduces the dimensionality of the data [53]. According to the idea of integrated learning, the RF collects multiple decision trees and averages the output of each decision tree to obtain the final output result, which measures the relative importance of each feature for feature selection. The $GINI$ index is taken as a measure of feature importance in the model, and the following formula calculates the $GINI$ index of node m:

$$GINI_m = 1 - \sum_{k=1}^{|K|} p_{mk}^2, \tag{1}$$

where K represents the number of categories and p_{mk} denotes the proportion of category k in node m. The $GINI$ index is the purity of the node; the larger the $GINI$ index, the lower the purity of the node, and the average change in the $GINI$ index serves as the level of importance of the feature.

The RF is adopted to select a subset of features retained in light of a preset feature threshold after the important features are obtained [54]. The following methods are commonly used for the selection of thresholds:

(1) Retention of feature indicators with importance scores greater than 0;
(2) Preservation of the first K feature indicators according to demand;
(3) Screening out feature indicators with less than 10% feature significance.

3.2.2. Partial Least Squares Structural Equation Modeling (PLS-SEM)

PLS-SEM is a composite-based approach to SEM that uses linear combinations of variables to explain the variance of the target constructs in the structural model [55]. It is one of the most powerful techniques for accounting for the correlation between many measurable and nonmeasurable factors. Suppose that there are J groups of observable variables, and that each group contains p_j variables. Thus, each group of observable variables can be expressed as $X_j = (x_{j1}, x_{j2}, \cdots, x_{jp_j}), (j = 1, 2, \cdots, J)$. Each group corresponds to a latent variable ξ_j, which is assumed to be normalized, i.e., the mean value is 0, and the variance is 1. Hence, each group of observable variables X_j and the corresponding latent variables ξ_j constitute a measurement model, also known as an external model. The structure model is a description of the different latent variables of causality, usually expressed as Formula (2) [36]

$$\xi_j = \sum_{i \neq j} \beta_{ij} \xi_i + \zeta_j, \tag{2}$$

where ζ_j is the random error term, and its mean value of the residuals is 0, which is uncorrelated with ξ_j, and where β_{ij} is the coefficient. Formula (2) shows that the interdependence among the latent variables can be considered a causal association model, which is a causal chain with no loops. The causal association model can be represented as a correlation matrix whose dimension is the number of latent variables. If latent variable j explains latent variable i, the element in the matrix takes a value of 1; otherwise, it takes a value of 0; thus, the matrix is also called the internal design matrix.

PLS regression can estimate latent variables in two ways. The first is to calculate latent variables based on the correlation between observable and latent variables, also known as an external estimation. The second way is to evaluate a specific latent variable using other latent variables [32], which is an internal estimation; the result is denoted as Z_j, which is shown in Formula (3):

$$Z_j = \left(\sum_{i, \beta_{ij}} e_{ij} Y_i \right)^*, \tag{3}$$

where "∗" denotes the standardization of the estimate, Y_i is the external estimate of the other potential variables, and e_{ij} is the internal weight, which is calculated by the following Formula (4):

$$e_{ij} = sign(r(Y_i, Y_j)) = \begin{cases} 1 & (r(Y_i, Y_j) > 0) \\ 0 & (r(Y_i, Y_j) = 0) \\ -1 & (r(Y_i, Y_j) < 0) \end{cases}, \tag{4}$$

where "$Sign$" refers to the sign function, and $r(Y_i, Y_j)$ denotes the correlation coefficient between the external weight estimates Y_i and Y_j. The weights for the internal estimates are calculated as follows:

$$W_j = \left(X_j^T X_j\right)^{-1} X_j^T Z_j, \tag{5}$$

where W_j is the coefficient after the normal least squares regression of Z_j.

The bootstrap method is used for statistical significance testing, but PLS-SEM has no underlying assumption that the data should be normally distributed, meaning parametric significance tests are not applicable for testing whether the coefficients are significant. Instead, the nonparametric bootstrap procedure is applied to PLS-SEM to test the statistical significance of the results, and parameter estimates (e.g., external weights, loadings, and path coefficients) are used to derive standard errors of the estimates. The GOF index can explain the model quality of the measurements and structural models, which are calculated as the geometric mean of the average communality and average R^2. The GOF is used to evaluate the quality of the model, and a GOF value greater than 0.7 indicates that the model performs well. Loadings reflect the correlation between latent and observed variables, and the observed variables with loadings below 0.7 should be deleted [56].

Cronbach's alpha (C. alpha) is the coefficient of reliability. When the data have a multidimensional structure, C. alpha is usually low. Dillon-Goldstein's rho (DG. rho) is used to evaluate the measurement effectiveness of the set of indicators for their corresponding underlying construct. Acceptable values above 0.7 for C. alpha and DG. rho indicate high reliability in the block of interest. Furthermore, the average variance extracted (AVE) is used to assess the convergent validity of the latent variables. The AVE values of all the constructs are greater than 0.5, confirming significant reliability and validity [57].

3.2.3. Entropy Weight Method (EWM)

The EWM is an unbiased weighting method that determines the weights of indicators according to the information provided by the indicators themselves, avoiding the negative impact of subjective factors and making the results more credible [58]. The entropy weight is the parameter that describes the differences in the evaluation objectives. The lower the entropy value, the more information is provided, and the higher the weight.

The first step is data normalization, as follows:

$$r_{ij} = \frac{x_{ij} - \min\{x_{ij}\}}{\max\{x_{ij}\} - \min\{x_{ij}\}}, \tag{6}$$

$$r_{ij} = \frac{\max\{x_{ij}\} - x_{ij}}{\max\{x_{ij}\} - \min\{x_{ij}\}}, \tag{7}$$

where Formula (6) is used to normalize the positive index. The larger the values, the better the model's efficacy. In contrast, Formula (7) is applied to the negative indicators, and smaller values are more desirable. In addition, r_{ij} is the normalized value, x_{ij} is the original value, and $\max\{x_{ij}\}$ and $\min\{x_{ij}\}$ represent the maximum and the minimum values in the dataset, respectively. The weight of each indicator H_i is determined via the entropy method [59], which is defined in Formula (8), and the coefficients f_{ij} and k are calculated by Formulas (9) and (10):

$$H_i = -k \sum_{j=1}^{n} f_{ij} \ln f_{ij}, \tag{8}$$

$$f_{ij} = r_{ij} / \sum_{j=1}^{n} r_{ij}, \tag{9}$$

$$k = 1/ \ln n, \tag{10}$$

where n is the number of evaluated objects. When $f_{ij} = 0$, we suppose that $f_{ij} \ln f_{ij}$ is also equal to 0.

The entropy weight [60] of each indicator w_i is then calculated using Formula (11):

$$w_i = (1 - H_i)/(m - \sum_{i=1}^{m} H_i), \tag{11}$$

where m is the total number of indicators. The carbon emissions score effectively measures low-carbon development by multiplying the entropy weight w_i by the dimensionless value r_{ij}. The indicators are summarized by the category layer, obtaining the score S_c for each, as shown in Formula (12):

$$S_c = \sum_{i=1}^{k} (w_i \times r_{ij}), \tag{12}$$

where S_c is the low-carbon development level score of the c-th category, and k is the number of the outermost indicators included in class c.

4. Results and Discussion

4.1. ARIMA Projection of Carbon Emissions in 2022

Because the carbon emission data of Shandong Province in 2022 have not yet been published, this study employs an autoregressive integrated moving average model (ARIMA) to forecast the value based on the time series data in Shandong Province, which shares the national carbon emissions from 1997 to 2021. This approach enhances accuracy compared with directly extrapolating the 2022 data from the historical carbon emissions of Shandong Province. Moreover, this paper applies the grid search method to find the optimal parameters, which are p = 1, q = 0 and d = 0, determined as ARIMA (1, 0, 0) with a prediction value of 0.0819, which is multiplied by the actual national carbon emission data from 2022; thus, we obtain the carbon emission data of Shandong Province in 2022, which are 939.5187 $MtCO_2$.

4.2. Analytical Results of PLS-SEM

This paper presents a four-level initial empirical indicator system of carbon emission influencing factors, which is shown in Figure 2.

The indicator system in Figure 2 includes 6 primary indicators of carbon emissions (CE), labeled in orange; 14 secondary indicators, labeled in yellow; 18 tertiary indicators, labeled in green; and 8 quadruple indicators, labeled in blue. The population (POP), economy (ECO), energy (ENE), main pollutants (MP), water resources (WR), and afforestation (AFF) are selected as latent variables for the CE. Initially, it is essential to ascertain the intrinsic relationships between the CE and the six latent variables. In addition, constructing paths between every two variables is crucial, where the path coefficients are calculated according to causality and correlation matrices. The literature shows that the POP influences the ECO [41,61], ENE [62], MP [63,64], WR [65] and AFF [66], and the ENE influences the ECO [67] and MP [68,69]. A PLS-SEM is constructed using the relationship between these latent and observable variables, the loadings of which are shown in Table 2.

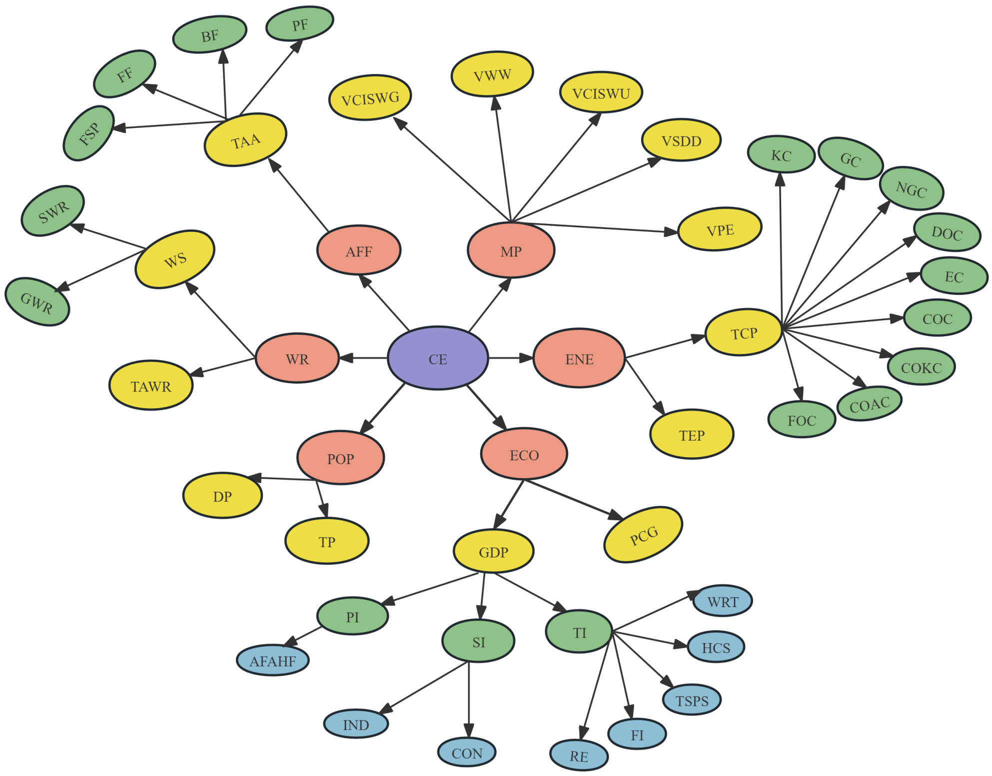

Figure 2. Carbon emission empirical indicator system.

Table 2. The external loadings between latent and observable variables in the PLS-SEM .

Variable Relation	Loading	Variable Relation	Loading
POP-TP	0.9980	MP-VCISWU	0.9830
POP-DP	0.9980	MP-VPE	−0.4780
ENE-TCP	0.6210	MP-VSDD	−0.8710
ENE-TEC	0.9690	MP-VWW	0.6870
ECO-GDP	1.0000	WR-TAWR	0.7230
ECO-PCG	1.0000	WR-WS	−0.8790
MP-VCISWG	0.9830	AFF-TAA	1.0000

Table 2 shows certain instances where the factor loadings between observable variables and their associated latent variables are less than 0.7, for which observable variables should be removed and the model rebuilt. After adjusting for variables, the GOF value is 0.8141, indicating that the indicators selected effectively construct the PLS-SEM, but the model precision can be further optimized.

4.3. Screening Results for RF

To further increase the GOF value and optimize its pathways, this study proposes an improved model named RF-PLS-SEM. First, the RF is used to select indicators in the carbon emission indicator system, where we set the screening threshold at 0.1, meaning indicators with feature importance less than 0.1 are excluded; otherwise, they are retained. The screening results at all levels are shown in Figure 3.

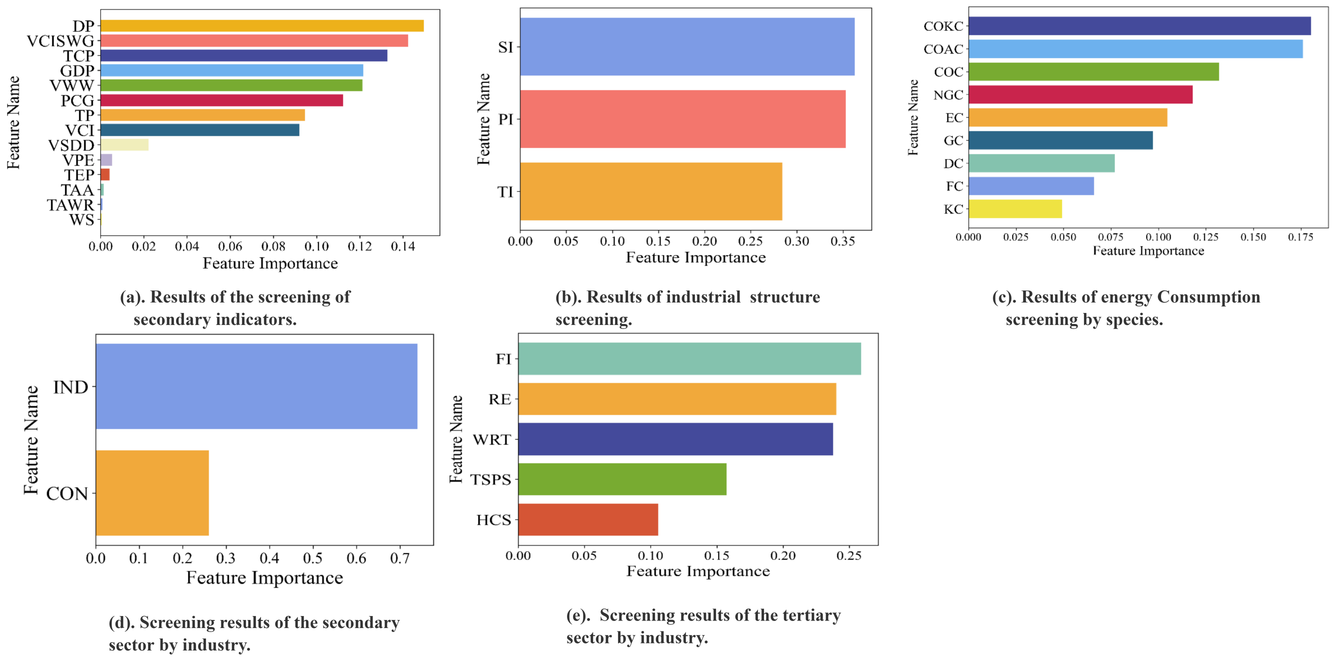

Figure 3. Feature screening results for RF.

In Figure 3, the horizontal axis represents feature importance, and the vertical axis represents the screened variable. Since the primary indicators are qualitative and feature screening requires actual data, thus CE is directly used to screen the secondary indicators. As illustrated in Figure 3a, the feature importance thresholds of the secondary indicators associated with the AFF and WR do not exceed 0.1. Consequently, the AFF and WR are excluded as primary indicators. In the existing literature, most studies were focused on cumulative afforestation area, which plays a significant role in carbon absorption. However, in this paper, we mainly consider the newly added afforestation area for the current year, which is sourced from the Shandong Statistical Yearbook. Since the photosynthetic capacity of new saplings is relatively low, their carbon sink effect is not significant in the initial stages. Therefore, the annual increase in afforestation area has a relatively low impact on carbon emissions. Furthermore, the rapid urbanization in Shandong Province has led to a decrease in afforestation areas. In a word, afforestation has a minimal impact on carbon emissions in Shandong Province. Moreover, the secondary indicators corresponding to the POP, ECO, ENE, and MP have not been completely eliminated; thus, these four primary indicators are retained. Similarly, the secondary indicators are utilized to screen the tertiary indicators, which are adopted to screen the quadruple indicators. Figure 3b,c show the screening results of the tertiary indicators. Specifically, Figure 3b show that the primary, secondary and primary industries (PI, SI, TI) are retained, and Figure 3c shows that coal (COAC), coke (COKC), crude oil (COC), natural gas (NGC), and electricity consumption (EC) are obtained, whereas diesel oil (DC), gasoline (GC), fuel oil (FC) and kerosene consumption (KC) are rejected. Figure 3d,e show the screening of the indicators at the fourth level, demonstrating the industry screening results for the secondary and tertiary industries, respectively, and none of the variables are excluded. The final indicator system is reconstructed per the above results as shown in Figure 4.

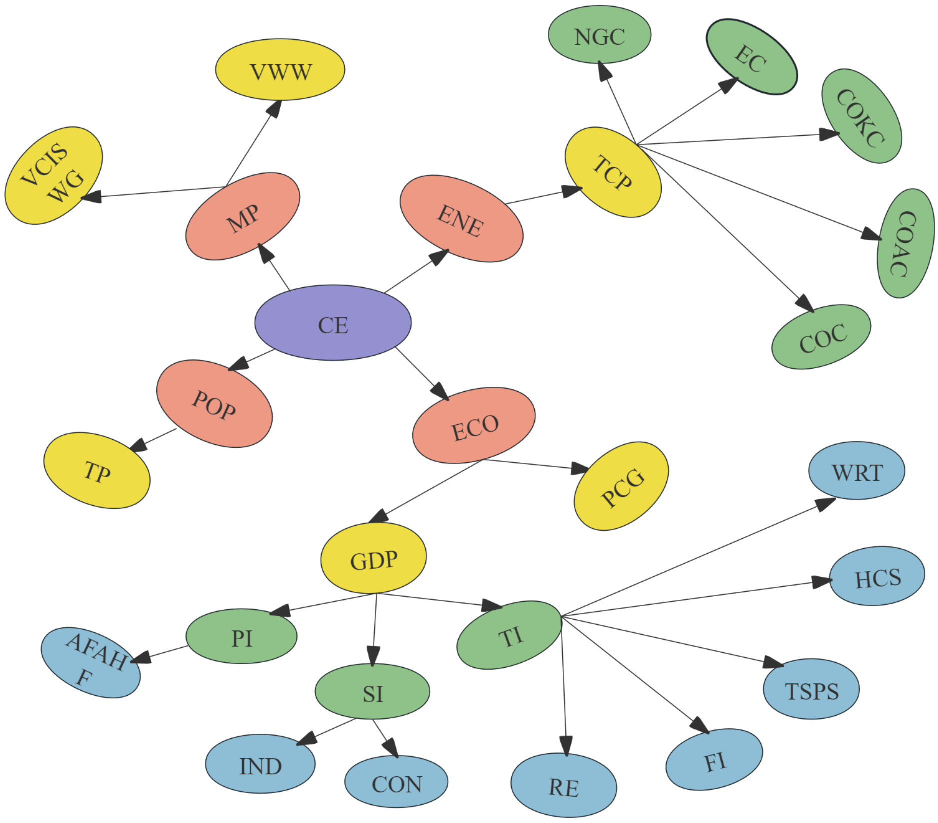

Figure 4. The system of terminal indicators.

Figure 4 shows that the main factors influencing carbon emission in Shandong Province can be categorized into four aspects: population, energy, economy and main pollutants. After screening, the analysis includes four primary indicators, six secondary indicators, seven tertiary indicators, and eight quaternary indicators.

This paper adopts the explained variance score (EVS), mean squared error (MSE), mean absolute error (MAE) and root mean square error (RMSE) to compare the accuracy of the initial indicator system with that of the renewable system based on the RF. A comparison of the model accuracy is shown in Table 3.

Table 3. Error comparison between the original and the reconstructed indicator system.

	EVS	MSE	MAE	RMSE
ENE-original	0.9411	0.0101	0.0774	0.1003
ENE-reconstructed	**0.9891**	**0.0007**	**0.0233**	**0.0257**
total-original	0.8645	0.0099	0.0565	0.0997
total-reconstructed	**0.9902**	**0.0018**	**0.0379**	**0.0424**

EVS is the number of [0, 1] values; the larger the value, the better its prediction effect. The MSE, MAE, and RMSE are applied to calculate the prediction error. The smaller the value, the better the prediction will be. As shown in Table 3, the accuracy of both the energy and the total indicator systems are improved significantly compared with those of the prescreening indicators.

4.4. Analytical Results of the RF-PLS-SEM

After the variables are screened according to the RF, the GOF value of the model is significantly improved to 0.9220. The structural equation path diagram between the CE and each latent variable constructed is shown in Figure 5.

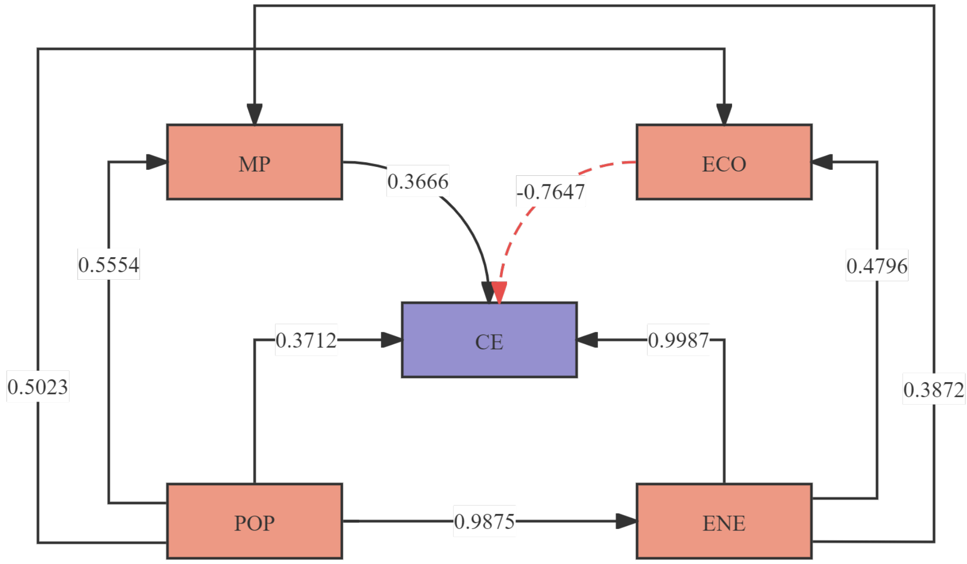

Figure 5. Latent variables path analysis of carbon emissions. Note: the paths representing positive influencing factors are depicted as solid black lines, whereas the paths for negative influencing factors are shown as red dashed lines.

As shown in Figure 5, POP, ENE, and MP positively impact CE, and the ECO negatively impacts CE. The POP, whose influence coefficient is 0.3712, has some influence on CE, suggesting that the density of population (DP) somewhat contributes to CE. The path coefficient between the ECO and CE indicators is −0.7647, meaning that carbon emissions decrease as the economy grows. The following study addresses the inhibitory effect of the ECO indicator on CE by decomposing the ECO indicator and constructing a new structural equation model in detail.

The ENE, measured by total consumption production (TCP), has the highest positive impact on CE, and the path coefficient is 0.9987, meaning that Shandong is the province that consumes the most energy in China, and high energy consumption is associated with its rapid economic development. In addition, in 2020, coal consumption accounted for 64% of Shandong Province's energy consumption structure, whereas clean energy consumption accounted for only 7.4%; thus, the issue of carbon emissions caused by energy consumption must be taken seriously.

In addition, the path coefficient of the MP and CE is 0.3666, indicating that the main pollutants have a positive influence on carbon emissions and that the volume of wastewater discharged (VWW) and of common industrial solid waste generated (VCISWG) have positive effects on the CE. The Ministry of Ecology and Environment noted that, in the context of "double carbon", water environmental management has once again become a key area for reducing carbon emissions [70]. Most recent estimates have shown that global WWTPs directly emit approximately 650 Gg CO_2e annually [14]. Moreover, owing to rapid industrialization, large amounts of industrial solid waste have been generated, resulting in different degrees of environmental pollution, such as carbon emissions. Shandong Province is a major industrial and chemical province, with more than 7200 enterprises producing chemical substances, making pollutant management more burdensome. The rational utilization of industrial solid waste can reduce carbon emissions during industrial production. Therefore, the resource utilization of industrial solid waste, such as fly ash, should receive increased attention from government departments [71].

Latent variables are linear combinations of observable variables. The 95% confidence interval is employed to determine whether the path coefficients are significant, and the test results are shown in Table 4.

Table 4. Statistical significance test for latent variables.

Variable	Estimate	Std. Error	T-Value	*p*-Value
Population	0.3710	0.2370	1.5700	0.1325
Energy	0.9990	0.2310	4.3300	0.0003
Economy	−0.7650	0.1670	−4.5800	0.0002
Main pollutants	0.3670	0.1000	3.6700	0.0014

As shown in Table 4, the P value between POP and CE is 0.1325, indicating that it fails to meet the threshold for statistical significance. However, this means that, as an indirect influencing factor, POP affects carbon emissions through the mediating variables. The rest of the variables pass the significance test, showing that the ENE measured by the TCP, the ECO by the GDP and the per capita GDP (PCG), and the MP measured by the VWW and the VCISWG are direct influencing factors. The loadings between the observed variables and their latent variables are shown in Table 5. The path loadings of the observable variables and their corresponding latent variables are all greater than 0.7, indicating that the model is effective.

Table 5. The external loadings between latent and observable variables in the RF-PLS-SEM.

Variable Relation	Loading	Variable Relation	Loading
POP-DP	1.0000	ECO-GDP	1.0000
ENE-COEC	0.9640	ECO-PCG	1.0000
ENE-COAEC	0.9240	MP-VCISW	0.9260
ENE-COKEC	0.9630	MP-VWW	0.8770
ENE-NGEC	0.9130		

Moreover, the model effectiveness test results are displayed in Table 6, showing that C.alpha and DG.rho are greater than 0.7, and that the AVE is greater than 0.5, indicating that the model has better reliability and validity. To summarize, the improved model shows a significant increase in the accuracy with the GOF value from 0.8141 to 0.9220 compared to the traditional PLS-SEM model. At the same time, some of the variable loadings in the original model are below 0.7 in Table 2, whereas all the loadings in the newly established model have been increased to above 0.7 in Table 5.

Table 6. Reliability and validity test of the RF-PLS-SEM model for latent variables.

Variable	C. alpha	DG. rho	AVE
POP	1.0000	1.0000	1.0000
ENE	0.9570	0.9690	0.8860
ECO	1.0000	1.0000	1.0000
MP	0.7730	0.8980	0.8130
CE	1.0000	1.0000	1.0000

4.5. Analytical Results of the RF-PLS-SEM after Decomposing Economic Indicators

The ECO is the negative indicator of CE, and the observed variables of the ECO are divided into PCG and GDP, while GDP includes primary industry (PI), secondary industry (SI), and tertiary industry (TI). To study which economic indicators hinder carbon emissions, this paper further analyses the pathways of carbon emission influencing factors, including decomposed economic variables. The RF-PLS-SEM model, which includes detailed economic variables and other influencing factors, has a GOF value of 0.9392, with all the variable loadings surpassing 0.8. The model demonstrates strong reliability and validity, as evidenced in Table 7. The results of the optimized path adjustment model are depicted in Figure 6. In addition, the PI and TI are negative indicators of CE, and both ENE and POP slightly hinder the TI.

Table 7. Effectiveness testing of the RF-PLS-SEM model for segmented variables.

Variable	C. alpha	DG. rho	AVE
DP	1.0000	1.0000	1.0000
TEC	0.9570	0.9690	0.8860
PCG	1.0000	1.0000	1.0000
SI	0.9810	0.9910	0.9810
PI	1.0000	1.0000	1.0000
TI	0.9940	0.9970	0.9950
POI	0.7730	0.8980	0.8120
CE	1.0000	1.0000	1.0000

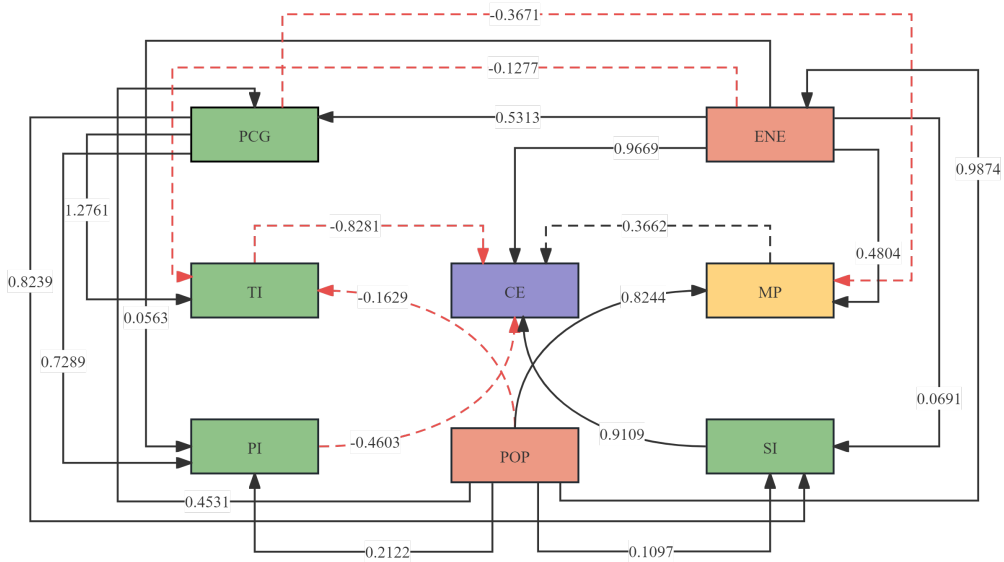

Figure 6. Path analysis of disaggregated economic indicators and carbon emissions and their influencing factors. Note: the paths representing positive influencing factors are depicted as solid black lines, whereas those for negative influencing factors are shown as red dashed lines.

The path coefficient of the PI and CE is −0.4603, indicating that primary industry inhibits the growth of carbon emissions. In China, the value added of primary industry mainly comes from agriculture, forestry, fishery, and animal husbandry. Urbanization has reduced the number of fishing grounds, thereby increasing CO_2 emissions [72], and long-term empirical statistics show that for every 1% increase in the negative impact of fishing vessels on aquatic organisms, the carbon intensity increases by 0.55%. The latest data prove that fishery factors play a role in reducing carbon emissions. Because fisheries not only emit fewer carbon emissions than animal husbandry, but also reduce carbon intensity by farming seaweed [73], they play an important role in reducing carbon emissions. Shandong Province is also very rich in fishery resources, with more than 2300 km of coastline and a sea area of over 500,000 square kilometers, and the marine fishery industry is one of the traditionally advantageous industries. Marine pasture is an important factor in absorbing carbon dioxide from the atmosphere [74] and has successfully addressed carbon emissions in China. Shandong Province is rich in various marine biological resources, such as seaweed and marine microorganisms, which can absorb and fix carbon dioxide. Shandong Province has been pushing forward the construction of modern marine ranches and currently has 67 national marine ranching demonstration zones, the most in the country.

The path coefficient of TI and CE is −0.8281, indicating that tertiary industries suppress the growth of carbon emissions. With the rapid development of e-commerce, the technological innovation capacity of modern service industries, such as information technology, has also significantly increased. Improvements to energy efficiency and innovation levels are the main driving force for upgrading production technology [75]. Tertiary industry gradually eliminates the excess production capacity of secondary industries, which helps reduce unnecessary industrial pollution emissions and has a significant inhibitory effect on carbon emission intensity. Research results show that tertiary industries, especially those that involve technological innovation activities, can stimulate more low-carbon and clean technology innovations [76].

The path coefficient of the POP and TI is −0.1629, meaning that when the population increases, the tertiary value added also decreases. Moreover, the tertiary industry has a negative effect on carbon emissions, while population has an indirect effect on carbon emissions, confirming that the population in Shandong Province slightly hinders the development of the tertiary industry, thereby indirectly affecting carbon emissions through the technological innovation capacity of the TI. According to the data obtained from the seventh population census in 2020, 11 provinces in China had an elderly population of 10 million, while Shandong's exceeded 20 million, making its elderly population the largest in the country, and indicating aging will continue to accelerate. The population of older adults in Shandong Province is growing rapidly, while the proportion of young and middle-aged people is declining annually, which poses challenges to traditional service industries that rely heavily on labor. Many emerging sectors within the tertiary industry require continuous technological innovation, but the population aging trend somewhat restricts enhancing innovation capabilities. This study revealed that the increase in population density in Shandong Province has a slight inhibitory effect on the development of tertiary industries. Therefore, actively developing the "silver economy" and establishing a sound elderly care service system (including health care, tourism, education, etc.) are crucial for promoting economic development within the tertiary industry. This approach transforms the adverse aspects of the increasing elderly population density into a favorable factor that drives economic growth. Furthermore, reducing talent loss in Shandong Province is crucial for achieving the optimal labor allocation in an aging society.

The path coefficient between ENE and TI is −0.1277, indicating that energy consumption not only directly affects carbon emissions, but also slightly inhibits the development of tertiary industries, which is unfavorable for innovating low-carbon clean technologies. The path coefficient between SI and CE is 0.9109, indicating it has a significant effect on CE. China's economy has long been overly dependent on secondary industries, which have become the economy's leading industrial sector. The development of secondary industries, especially the manufacturing industry, tends to consume more resources and emit more carbon dioxide than tertiary industries. Therefore, to achieve sustainable economic development, Shandong Province must change its economic development mode as soon as possible and increase the proportion of tertiary industries.

4.6. Low-Carbon Development Level Score

Low-carbon development is a multiobjective issue that seeks not only to reduce greenhouse gas emissions but also to ensure economic growth. Low-carbon development is a complex dynamic system, and the subsystems are interconnected, interact, and constrain one another [77]. The carbon emission indicator system covers the population, economy, energy, and ecology, is comprehensive and systematic, and can be used to evaluate the current status of the low-carbon development level in Shandong Province. The indicators screened are of greater fitness by quantitative analysis, and they are positive or negative indicators according to the path coefficients; thus, the evaluation results are highly convincing. Moreover, there is an inverse relationship between the level of low-carbon development and carbon emissions; that is, if a factor has a positive effect on carbon emissions, it will have a negative effect on the sustainable development score, and vice versa. Influential factors obtained using the RF-PLS-SEM are applied to the EWM to calculate the low-carbon development score in Shandong Province; the results are shown in Table 8.

Table 8. Weights and directions of subsystem indicators.

Subsystems	Indicator	Weight	Direction
POP	DP	0.0498	−
	PCG	0.0759	+
ECO	AFAHF	0.0749	+
	CON	0.0056	−
	IND	0.0593	−
	WRT	0.0978	+
	TSPS	0.0774	+
	HCS	0.0799	+
	FI	0.1280	+
	RE	0.0913	+
ENE	COAC	0.0867	−
	COKC	0.0361	−
	COC	0.0324	−
	NGC	0.0210	−
	EC	0.0367	−
MP	VWW	0.0199	−
	VCISWG	0.0274	−

The weights of the indicators in Table 8 are used to calculate the low-carbon development level score. The plus and minus signs represent the direction of the effect of each indicator on low-carbon development based on the quantitative analysis of the RF-PLS-SEM, respectively. The higher the score, the greater the effect of a low-carbon development level from 1997 to 2021; the results are shown in Figure 7.

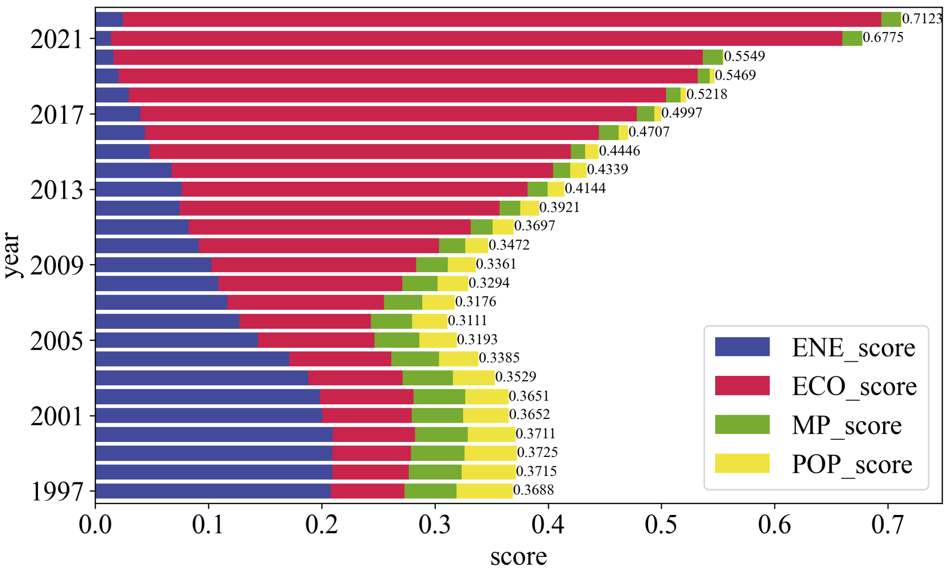

Figure 7. Low-carbon development level score by subsystem.

In Figure 7, the POP_score, ECO_score, ENE_score, and MP_score represent the scores for population, economy, energy, and main pollutants, respectively; the larger the area of the bar, the higher the indicator score for that year. The ENE_score in Shandong Province was higher and more stable from 1997 to 2000, with a decline to approximately 2001 and a significant drop after 2005. The proportion of POP_score and MP_score of the total score gradually decrease for the low-carbon development level. The ECO_score also shows the opposite state of change compared with the ENE_score. In addition, the level of economic development barely increased before 2005 and then slowly increased. After 2011, the growth rate increased dramatically, and the economy reached the level of low-carbon development in Shandong Province. To adapt to the new development situation in recent years, Shandong Province has been promoting industrial upgrading, continuously eliminating backward production capacity and high energy-consuming production capacity and promoting the economy to better embrace the new era. The overall score trend of the low-carbon development level in Shandong Province is shown in Figure 8.

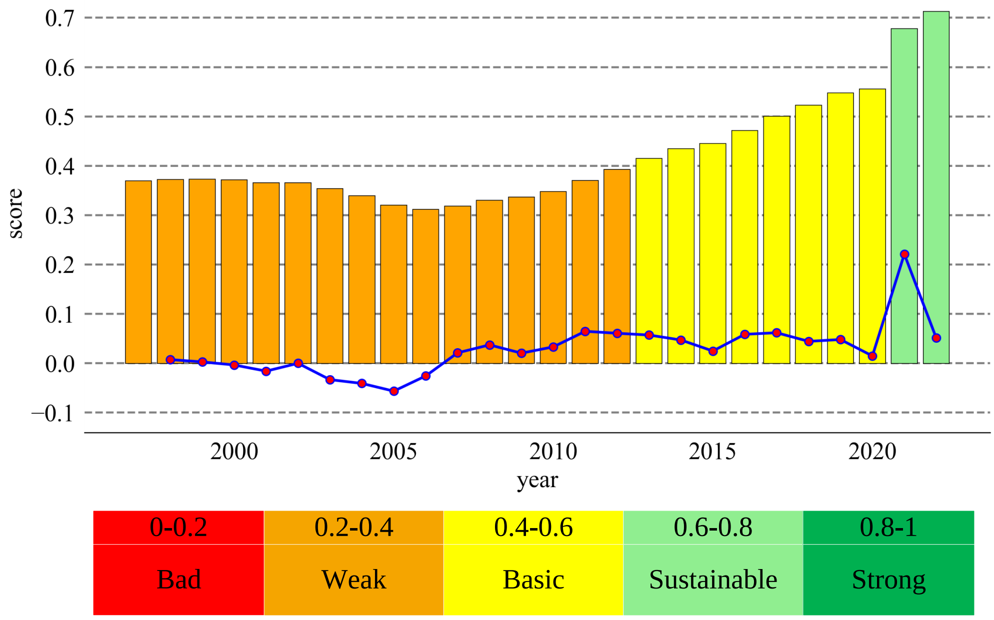

Figure 8. Overall score for the level of low-carbon development. Note: The blue line graph represents the growth rate of the low-carbon development level score.

As shown in the bar chart in Figure 8, the low-carbon development level score of Shandong Province remained stable in the early stage from 1997 to 2000, then began to decline in 2001, and reached its lowest value in 2006. However, it began to increase in 2007, and continued increasing until 2022. The line graph represents the growth rate of the low-carbon development level score, which reveals an initial downward trend, with a negative growth rate from 2000 to 2006 and a negative peak in 2005. Drawing on previous research results, the level of low-carbon development is divided into five stages on average: poor, weak, basic, sustainable and strong, with an overall threshold value of [0, 1] [60]. According to the calculations, the stages of low-carbon development were weak, basic, and sustainable during the 1997–2012, 2013–2020, and 2021–2022 periods, respectively. Moreover, 2021 is an important turning point toward sustainable development, which is the opening year of the "14th Five-Year Plan". Shandong Province focused on transforming and upgrading traditional energy to achieve positive results. Specifically, investment in high-tech industries grew by 11.6%, crude steel production increased by 12.59 million tonnes, and new and renewable energy generation capacity reached 100.6 billion kilowatt-hours. The quality development of Shandong Province was on the hoof in 2022, and innovation-driven results were significant.

5. Conclusions and Policy Implications

This paper presents a four-level indicator system for the influencing factors of carbon emissions, and proposes an improved RF-PLS-SEM model, combining the EWM to analyze the influencing factors of carbon emissions in Shandong Province. The results demonstrate that population, economy, energy, and main pollutants have greater impacts on carbon emissions, whereas water resources and afforestation have relatively lower impacts. Furthermore, the improved model shows a significant increase in accuracy, with the GOF value increasing from 0.8141 to 0.9220 compared with the traditional PLS-SEM. The specific conclusions and policy recommendations of this paper are as follows:

(1) The primary and tertiary industries in Shandong Province negatively influence carbon emissions, and the secondary industry significantly contributes to carbon emissions. As one of the larger marine provinces, Shandong Province has abundant marine and fishery resources, and has pushed forward the development of modernized marine pastures, which can help reduce carbon emissions; thus, primary industry plays an important role in reducing carbon emissions. It is essential to develop its advantages in marine and fisheries, promote green development and the upgrading of fisheries, conserve aquatic biological resources, etc., which can also provide some references for other regions with marine resources in Shandong Province. In addition, tertiary industries restrict carbon emissions, but secondary industries significantly promote carbon emissions; thus, accelerating the upgrading of the industrial structure and increasing the proportion of tertiary industries in the national economic system are crucial. Moreover, expanding fiscal subsidies and investment channels for green finance can have a positive effect on realizing the "dual carbon" goals in Shandong Province.

(2) The population density in Shandong Province has an indirect influence on carbon emissions and slightly inhibits the development of tertiary industries. Shandong Province's aging population presents both challenges and opportunities for the economic development of tertiary industries. By formulating scientific response strategies and measures, we can fully leverage the market opportunities presented by population aging and actively develop a "silver economy" tailored to the demand characteristics of the elderly population, covering multiple sectors, such as pensions, health care, tourism, and education. By providing diversified products and services to meet the consumption needs of elderly individuals, we can drive the tertiary industry's transformation, upgrading, and high-quality development.

(3) Energy, measured by total consumption production, has the greatest positive impact on CE; this not only directly accelerates carbon emissions, but also slightly inhibits the development of tertiary industries, which is adverse for the innovation of low-carbon clean technologies. Shandong Province has vigorously developed its economy with increasing energy consumption, which has led to environmental deterioration; however, this issue has improved with the proposal of sustainable development policies. Shandong Province can adhere to the concept of green development in resource recycling. In addition, promoting a cleaner and low-carbon energy transition and curbing the development of high-energy consumption and high-emission projects can result in a win–win outcome of reducing energy consumption and developing the economy.

(4) Of the main pollution-influencing factors in Shandong Province, the volume of discharged wastewater and common industrial solid waste generated has a direct and positive influence on carbon emissions. The wastewater treatment industry accounts for the largest share of the environmental protection industry; therefore, policies should be formulated to promote energy-efficient products and equipment and accelerate eliminating old and inefficient equipment. Moreover, the output and trend of solid waste must be assessed by local departments, policies related to solid waste should be formulated, and facilities for solid waste treatment should be constructed in Shandong Province.

(5) The scores at different stages of low-carbon development in Figure 8 show a trend of steady progress, decline, and then growth. Specifically, the trend was weak, basic, and sustainable in the 1997–2012, 2013–2020, and 2021–2022 periods, respectively, Moreover, the growth rate of the scores from 2000 to 2006 is negative, whereas those of the other years are positive. According to the results of the low-carbon development

level assessment, the inhibitory effect of economic factors on carbon emissions must be enhanced in Shandong Province. Moreover, reducing energy consumption and pollution, accelerating industrial upgrading, and promoting green technological innovation are pivotal to achieving the target of reducing carbon emissions as soon as possible.

This paper mainly focuses on the influencing factors of carbon emission, carbon emission mechanisms and the low carbon development level in Shandong Province, and the results will not only provide a scientific basis for Shandong Province to draw up carbon emission policies, but also help Shandong Province to achieve the peak carbon goal by 2030. Furthermore, it will provide some references for other provinces and regions. As we know, the prediction of carbon emission intensity is one of the hottest issues. In the future, we will focus on the prediction of carbon emission intensity according to the improved neural network algorithm. Additionally, we will also consider the impact of extreme weather and policies on carbon reduction strategies.

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