Analysis of Influential Factors of Low-Carbon Economy in Heilongjiang Province Based on the Principal Component Analysis Method

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Abstract: Realizing carbon peak carbon neutrality is an inherent requirement for promoting high-quality development, and in the face of global climate change challenges, the development of a low-carbon economy has become a key strategy. As a key forest area, Heilongjiang Province still faces many challenges in low-carbon transformation. In this paper, by constructing the evaluation model of the level of low-carbon economic development, 4 secondary indicators and 16 tertiary indicators were constructed, followed by the use of Pearson coefficient correlation, which eliminated the explanatory variables that had little influence on the explanatory variables, and then the use of principal component analysis, which reduced the 13 explanatory variables into two principal components. It was found that education expenditure, gross regional product, urban sewage treatment rate and the number of public transportation vehicles per 10,000 people in the city were important influences on the low carbon economy. In response to these concerns, suggestions are made to optimize the industrial energy structure, encourage low-carbon technological innovation, formulate low-carbon development policies, and enhance public awareness of low-carbon.

1. Introduction

The report of the Twentieth Party Congress points out that realizing carbon peak carbon neutrality is an inherent requirement for implementing the new development concept, constructing a new development pattern, and promoting high-quality development, and it is an extensive and profound economic and social systematic change with great practical significance and far-reaching historical significance[1]. In today's world, global climate change poses an unprecedented challenge to human society, and low-carbon economy, as a new model of sustainable development, has become an important strategy to cope with climate change on a global scale. As of January 2023, a total of 28 carbon trading systems are in force globally and more than 20 are under development or design[2]. China, as the largest developing country, is also actively taking action, building a policy system centered on the Opinions on the Complete and Accurate Implementation of the New Development Idea and Doing a Good Job of Carbon Peak Achievement and Carbon Neutrality, and reviewing and adopting the Opinions on the Promotion of the Progressive Transfer of Dual Controls of Energy Consumption to Dual Controls of Carbon Emissions, to provide policy support for the green transition. As of December 31, 2023, the cumulative turnover of carbon emission allowances in the national carbon market was 4.42 million tons, with a cumulative turnover of 24.919 billion yuan[3]. As a national key forest area, the development of low-carbon economy in Heilongjiang Province is of great significance in promoting the optimization of regional economic structure, enhancing energy use efficiency, and promoting environmental protection and ecological construction. However, in the government report, the development of low-carbon economy in Heilongjiang Province in 2023 is not satisfactory. As a traditional heavy industry base, Heilongjiang Province faces greater challenges in transforming its high-energy-consuming and high-emission industrial structure into a green and low-carbon one; on the other hand, because the supervision and incentive mechanism at the national level is not yet perfect, resulting in insufficient local efforts to implement green and low-carbon policies,

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and the endogenous impetus and market vitality of the low-carbon transformation has not been sufficiently stimulated, the development of a low-carbon economy in Heilongjiang Province is in urgent need of further optimization.

Based on this, this paper firstly constructs the evaluation model of low carbon economy development level, with 4 secondary indicators and 16 tertiary indicators. Then the Pearson coefficient correlation is used to eliminate the explanatory variables that have little influence on the Y-value explanatory variables. Next, using principal component analysis, the 16 tertiary indicators are downscaled into two principal components. The results found that education expenditure, gross regional product, urban sewage treatment rate and the number of public transportation vehicles per 10,000 people in the city are important influencing factors in order to achieve the role of advising the government.

2. Literature review

2.1. Studies on Factors Affecting the Low-carbon Economy

Gregor Semieniuk[4] analyzed whether the imposition of unilateral anti-dumping tariffs helps countries that impose value to shift more of the value chain to their own countries. Khanna N, Fridley D and Hong L[5] conducted an ex-ante comparative assessment of the low-carbon development plans and supporting measures formulated by each of the 2010 low-carbon pilot cities. Pan A, Zhang W and Shi X et al.[6] used entropy balance-difference method to assess the impact of China's LCCP program on low-carbon innovation in Chinese prefecture-level cities. Lin J, Jacoby J and Cui S et al.[7] used decomposition method to combine the urban carbon intensity indicator with the low-carbon city indicator system to provide a better method for carbon intensity reduction performance evaluation. In terms of measuring the influencing factors of low-carbon economy, Chinese scholars mostly use entropy weight method and regression model to measure the evaluation index system of low carbon economy.

In terms of measuring the influencing factors of low carbon economy, Chinese scholars mostly use entropy weight method and regression model to measure the evaluation index system of low carbon economy. Liu Chao and Zhao Tao[8] used explanatory structural modeling to find out the key factors hindering the development of China's low-carbon economy. Zhou Yuanchun and Zou Ji[9] used Log Mean Divisia Factor Decomposition to quantitatively analyze and put forward suggestions for the development of low carbon economy. Xie Zhixiang, Yao Chen and Shen Wei[10] used DEA model and Malmquist total factor productivity index and Tobit regression model to analyze the influencing factors of the development performance of low-carbon economy. Sun Jingshui, Chen Zhirui and Li Zhijian[11] conducted an empirical study on the main influencing factors and contribution rate for the development of low-carbon economy in China based on the extended Stirpat model.

2.2. Trends in the Development of a Low-carbon Economy

Kapsalyamova Z, Mezher T and Al Hosany N et al.[12] found that the business environment affecting the cost of doing business tends to have a greater impact on the decision of firms to relocate to a low-carbon city. Wang J T, Zhou Y and Cooke F L[13] provided a systematic overview of the low-carbon economy, revealing the role and impacts of low-carbon economic policies on the energy future. Hunjra A I, Zhao S and Goodell J W et al.[14] verified that China's Big Data Comprehensive Pilot Zone policy promotes low-carbon innovation among firms. Wang C, Engels A and Wang Z[15] assessed the current literature on the potentials and barriers to China's transition to low-carbon development and proposed a research agenda to systematically address these shortcomings.

Zhuang Guiyang[16] proposed that China must establish a long-term mechanism for the development of low-carbon economy. Zhao Qiguo and Qian Haiyan[17] proposed countermeasures to develop low-carbon agriculture as well as specific measures. Yin Xiguo and Huo Ting[18] found that carbon emission reduction would not have a negative impact on economic growth, and that the levy of carbon tax and carbon trading system are the main institutional arrangements for realizing a low-carbon economy at present. Fan Decheng, Wang Shaohua and Zhang Wei[19] extracted the main influencing factors of primary energy consumption structure through literature review, and clarified the influencing mechanism through path analysis.

2.3. Review of the Literature Review of the Low Carbon Economy

To summarize, foreign scholars are more likely to use macro-analytical means, focusing on the role and impact of low-carbon economic policies, as well as the synergistic development of low-carbon innovation and the digital economy, while exploring the universal problems and solutions of the low-carbon economy from a global perspective. Domestic scholars are more inclined to use quantitative analysis methods to explore in depth the barriers and key factors to the development of low-carbon economy in specific industries or fields, and put forward specific policy recommendations. However, few scholars have analyzed the influencing factors of low carbon economy in local areas of the country. In addition, most scholars mostly use the data of the previous five years, the data is not timely, and the research is not of practical significance. Based on this, this paper first constructs a structural model of the influencing factors of low carbon economy, and then uses a combination of Pearson's coefficient correlation and principal component analysis to explore an important principal component factor affecting the low carbon economy, and to provide practical guidance for the development of low carbon economy in Heilongjiang Province.

3. Pearson Coefficient Correlation

Pearson correlation coefficient, is a measure of the degree of linear correlation between two variables. It was proposed by British statistician Karl Pearson.

Pearson's correlation coefficient ranges from -1 to 1. When the correlation coefficient is +1, it means that there is a perfect positive linear relationship between the two variables; when the correlation coefficient is -1, it means that there is a perfect negative linear relationship between the two variables; and when the correlation coefficient is 0, it means that there is no linear relationship between the two variables.

The formula for calculating the Pearson correlation coefficient is:

$$r = \frac{\sum (X-\overline{X})(Y-\overline{Y})}{\sqrt{\sum (X-\overline{X})^2 \sum (Y-\overline{Y})^2}} \tag{1}$$

3.1. Indicator Construction and Data Sources

As shown in Table 1, the first-level indicator is green GDP, and there are four second-level indicators, namely economic factors, environmental and resource factors, social factors, and financial factors. There are 16 tertiary indicators, namely gross regional product, education expenditure, turnover in the technology market, and so on.

Table 1 Indicator construction table.

First-level indicator	Second-level indicator	Tertiary indicator
Green GDP	Economic factor	Gross regional product (billions of dollars)
		Education expenses ($ million)
		Technology market turnover (billions of dollars)
		Total exports from domestic sources (thousands of dollars)
	Environmental and resource factor	Apparent carbon emissions (mt)
		Total energy consumption (tons of standard coal)
		Energy consumption elasticity coefficient
		Urban sewage treatment rate (%)
		Sulfur dioxide emissions (tons)
		Investment in environmental pollution control as a share of GDP (%)
		Forest coverage (%)
		Forest stock (million cubic meters)
	Social factor	Per capita green space in parks (square meters per person)
		Public transportation vehicles per 10,000 people in cities (standard units)
	Financial factor	Expenditures on energy conservation and environmental protection in local public financial expenditures (billion yuan)
		Value added index of the secondary sector

The data sources of this paper are highly credible, all from the Cathay Pacific database (www.baidu.com), Google Scholar search site (https://scholar.google.com/), National Bureau of Statistics (data.stats.gov.cn), China Carbon Accounting Database (http://www.ceads.net. cn/data), etc., with data years 2005-2022.

3.2. Pearson Correlation Coefficient Empirical Analysis

After setting up the correlation coefficients, the output is shown in Table 2:

Table 2 Pearson correlation coefficient.

Tertiary indicators	Explanatory variable	Correlation coefficient
X_1	Apparent carbon emissions (mt)	0.668**
X_2	Total energy consumption (tons of standard coal)	0.703**
X_3	Per capita green space in parks (square meters per person)	0.883**
X_4	Energy consumption elasticity coefficient	-0.554*
X_5	Gross regional product (billions of dollars)	0.957**
X_6	Education expenses ($ million)	0.967**
X_7	Technology market turnover (billions of dollars)	0.930**
X_8	Public transportation vehicles per 10,000 people in cities (standard units)	0.927**
X_9	Urban sewage treatment rate (%)	0.953**
X_{10}	Total exports from domestic sources (thousands of dollars)	0.572*
X_{11}	Value added index of the secondary sector	-0.819**
X_{12}	Investment in environmental pollution control as a share of GDP (%)	-0.527*
X_{13}	Sulfur dioxide emissions (tons)	-0.905**
X_{14}	Expenditures on energy conservation and environmental protection in local public financial expenditures (billion yuan)	0.865**
X_{15}	Forest coverage (%)	-0.841**
X_{16}	Forest stock (million cubic meters)	0.945**

Note: ** At the 0.01 level (two-tailed), the correlation is significant.
* Correlation is significant at the 0.05 level (two-tailed).

The results in the table show that the correlation coefficients of total exports from domestic sources, the elasticity coefficient of energy consumption, and the share of investment in environmental pollution control in GDP are less than 0.6, which indicates that their relationship with the explanatory variables is less than moderately correlated, which means that they have a lesser degree of influence on green GDP, and the correlation is insignificant, so they should be excluded. The correlation coefficients of other variables are all greater than 0.6, indicating that their relationship with the explanatory variables is more than moderately correlated, which means that they have a greater degree of influence on the green GDP, and the correlation is significant, which should be retained and can be further subjected to principal component analysis.

4. Principal Component Analysis (PCA)

4.1. Principles of Principal Component Analysis

PCA is a dimensionality reduction technique whose core objective is to extract a number of linearly uncorrelated variables from the original dataset, which are referred to as principal components. PCA determines the principal components by maximizing the variance of the data, thus preserving the most important information in the dataset. The specific implementation steps are as follows::

4.1.1. Construction of the Correlation Coefficient Matrix

At the initial stage, calculate the correlation coefficient matrix $R=(r_{ij})_{n\times p}$.

4.1.2. Eigenvalue and Eigenvector Solving

Further solve for the eigenvalues λ of the correlation coefficient matrix $R=(r_{ij})_{n\times p}$ and the corresponding eigenvectors a_j.

4.1.3. Calculation of Contribution Margin and Cumulative Contribution Margin

$$e_i = \frac{\lambda_i}{\sum_{i=1}^{p} \lambda_i} \tag{2}$$

$$E_m = \frac{\sum_{i=1}^{m} \lambda_i}{\sum_{i=1}^{p} \lambda_i} \tag{3}$$

4.1.4. Calculation of PCA

$$z_m = a_{mj} x_j \tag{4}$$

4.1.5. Selection of Principal Components

Based on the cumulative contribution ratio, select the principal components that explain most of the variance in the data. Typically, the selected principal components are considered to be sufficiently representative of the main information in the original dataset when the cumulative contribution rate is 85% or higher.

4.2. Empirical Testing

4.2.1. KMO and Bartlett's Test of Sphericity

The KMO test and the Bartlett's sphericity test are two tests commonly used to assess the applicability of data prior to factor analysis.

The KMO test is used to assess whether the correlation between the variables in a dataset is sufficient for factor analysis. The KMO value ranges from 0 to 1. The closer the KMO value is to 1, the stronger the correlation between the variables. 1, the stronger the correlation between the variables, and when the KMO value is greater than 0.6, it is more suitable for factor analysis.

Bartlett's Test of Sphericity is designed to be used to test for the existence of correlation between variables. The statistic of the test is the Chi-square, which is calculated as follows:

$$\chi^2 = \frac{n \cdot \sum_{i<j} (r_{ij} - \overline{r})^2}{1 + \frac{n-1}{2}} \tag{5}$$

In this formula, n is the number of variables, r_{ij} is an element in the correlation coefficient matrix, and $\overline{r}$ is the average of the correlation coefficients.

The KMO values and Bartlett's test of sphericity obtained are shown in Table 3:

Table 3 KMO values and results of Bartlett's test of sphericity.

KMO Sample Suitability Quantity		0.795
Bartlett's test of sphericity	Approximate chi-square	408.762
	Degrees of freedom	78
	Significance	0.000

As shown in Table 3, the KMO value is equal to 0.749 > 0.6, which allows the next step of principal component analysis.

4.2.2. Empirical Analysis

Use Spss26.0 software through the following steps “analysis - dimensionality reduction - factors”, and then carry out principal component analysis to get a principal component analysis of the variance explained table. The explained variance table is shown in Table 4.:

Table 4 Explanation of variance table.

Component	Total	Percentage of initial eigenvalue variance	Accumulation (%)	Total	Percentage of intercept squares and variances extracted	Accumulation (%)
1	10.859	83.533	83.533	10.859	83.533	83.533
2	1.075	8.268	91.802	1.075	8.268	91.802
3	0.407	3.134	94.936			
4	0.227	1.745	96.680			
5	0.139	1.070	97.750			
6	0.098	0.752	98.502			
7	0.076	0.583	99.085			
8	0.058	0.450	99.535			
9	0.029	0.225	99.760			
10	0.020	0.154	99.914			
11	0.007	0.056	99.970			
12	0.002	0.019	99.989			
13	0.001	0.011	100.000			

Extraction method: principal component analysis.

From the principal components variance interpretation table, the first and second principal components explain 91.802% of the total variance, indicating that the extracted first and second principal components can represent 91.802% of the total information of the original 13 green GDP explanatory variables. Therefore, two principal components should be extracted as F1 and F2. From the table of principal components variance explained, the first and second principal components explained 91.802% of the total variance, in addition, a scree plot was drawn as shown in Figure 1 below:

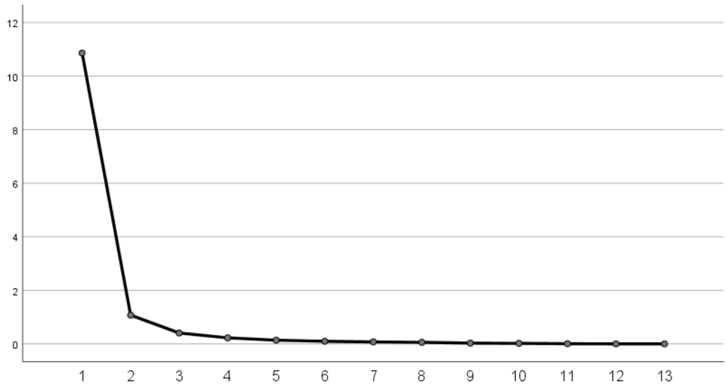

Figure 1 Scree plot.

From the scree plot, it can be seen that the slopes of principal component 1 and principal component 2 are larger, and the larger the slope, the more information is represented to be included, so it is said that the first and the second principal components should be extracted, and then a table of the score coefficients was obtained, as shown in Table 5:

Table 5 Component matrix.

	Principal Component 1	Principal Component 2
X1	0.810	-0.549
X2	0.838	0.491
X3	0.951	0.239
X5	0.988	0.036
X6	0.992	-0.075
X7	0.841	-0.271
X8	0.967	-0.117
X9	0.968	-0.132
X11	-0.839	0.294
X13	-0.829	0.464
X14	0.934	0.020
X15	0.938	0.212
X16	0.955	-0.130

Extraction method: principal component analysis.
2 components were extracted.

Two principal component formulas are obtained based on Table 5, which are:

$$F_1=0.810X_1+0.838X_2+0.951X_3+0.988X_5+0.992X_6+0.841X_7+0.967X_8+0.968X_9-0.839X_{11}-0.829X_{13}+0.934X_{14}+0.938X_{15}+0.955X_{16} \tag{6}$$

$$F_2=-0.549X_1+0.491X_2+0.239X_3+0.036X_5-0.075X_6-0.271X_7+-0.117X_8-0.132X_9+0.294X_{11}+0.464X_{13}+0.020X_{14}+0.212X_{15}-0.130X_{16} \tag{7}$$

5. Conclusion

(1) The four indicators with the greatest impact factors on the low-carbon economy are education expenses, gross regional product, urban sewage treatment rate and the number of public transportation vehicles per 10,000 people in the city, with values of 0.992, 0.988, 0.968 and 0.967, respectively.

Among other things, the increase in education funding fosters more talents with environmental awareness and knowledge of low-carbon technologies, which can promote the research and development and application of low-carbon technologies and accelerate the development of a low-carbon economy[20]. The growth of GDP often represents that the economy and the environment will develop positively at the same time, i.e., the green industry will flourish or the efficiency of resource utilization will be significantly improved. Increasing the urban sewage treatment rate helps to reduce the waste of water resources, which is important for reducing energy consumption[21]. Increasing the number of public transportation vehicles can effectively reduce energy consumption and carbon emissions, and promote the city's transition to a low-carbon economy.

(2) The indicators that have a relatively large impact on the low-carbon economy are forest stock, per capita green space in parks, forest coverage and expenditures on energy conservation and environmental protection in local public financial expenditures, with values of 0.955, 0.951, 0.938 and 0.934, respectively.

Among other things, an increase in forest stock will help to enhance this natural carbon sink function, which is essential for maintaining ecological balance and promoting low-carbon emission reduction. The increase in per capita park green space can improve the greening level of cities, which is in line with the development goal of low-carbon economy. Forests can absorb carbon dioxide in the atmosphere through photosynthesis[22], and increasing forest coverage can help enhance this natural carbon sink function. The increase of energy conservation and environmental protection expenditures in local public financial expenditures can guide more social capital to invest in energy conservation and environmental protection.

(3) Indicators with a moderate impact on the low-carbon economy are technology market turnover, total energy consumption and apparent carbon emissions, with values of 0.841, 0.838 and 0.810, respectively.

The increase in the turnover of the technology market reflects the active degree of technology transactions, and the prosperity of the technology market contributes to the promotion and application of new technologies, thus reducing energy consumption and carbon emissions. The increase in total energy consumption, if accompanied by the optimization of energy structure, effectively reduces carbon emissions by increasing the proportion of clean energy and renewable energy in energy consumption[23]. The implementation of monitoring and control of apparent carbon emissions can effectively promote the transition of the economy to a low-carbon model.

(4) The indicators with the smallest impact on the low-carbon economy are sulfur dioxide emissions and the value added index of the secondary industry, with values of -0.829 and -0.839, respectively, and with a negative impact.

Among them, although sulfur dioxide is a pollutant, its direct impact on climate change is small compared with greenhouse gases (e.g., carbon dioxide). The value added index of the secondary industry mainly reflects the scale and efficiency of industrial production, while the low-carbon economy pays more attention to energy consumption and carbon emissions[24]; moreover, part of the secondary industry realizes energy saving and emission reduction through technological innovation and industrial upgrading, and then the growth of its value added is also consistent with the goal of low-carbon economy.

Moreover, sulfur dioxide emissions and the value added index of the secondary industry have a negative impact on the low-carbon economy. It is found that sulfur dioxide emissions exacerbate environmental problems, which not only threaten human health and biodiversity, but also increase the burden on the government and society and affect the sustainable development of the economy. The increase in the value added index of the secondary industry may be associated with the increase in energy consumption and the rise in carbon emissions[25], and this growth may lead to the intensification of the contradiction between economic development and environmental protection.

6. Suggestion

6.1. Optimizing Industrial Energy Structure and Enhancing Energy Efficiency

In order to promote the development of a low-carbon economy, governments and enterprises should commit themselves to optimizing the energy structure, actively promoting the use of renewable energy sources such as solar energy, wind energy and hydropower, and at the same time improving the efficiency of energy use through technological innovation and management improvement.

6.2. Promoting Industrial Restructuring and Encouraging Low-carbon Technological Innovation

Through policy incentives and financial support, the Government can promote the adjustment of the industrial structure and encourage the development of low-carbon and environmentally friendly industries. At the same time, it should increase investment in research and development of energy-saving and emission reduction technologies, cleaner production technologies and resource recycling technologies.

6.3. Formulating Low-carbon Development Policies and Strengthening Environmental Regulations

The Government should clarify the objectives of low-carbon development and the path of emission reduction through legislation and policy guidance. At the same time, the government needs to strengthen the enforcement of environmental regulations to ensure that all economic activities comply with environmental standards and reduce pollutant emissions.

6.4. Raising Public Awareness of Low-carbon and Cultivating Low-carbon Professionals

The education sector should integrate environmental protection and low-carbon concepts into the education system at all levels, and enhance students' and the public's awareness of climate change and low-carbon lifestyles through curricula, publicity activities and social practices. At the same time, institutions of higher education should offer courses related to low-carbon economy, environmental science, energy engineering and other related subjects, and train talents with low-carbon technology research and development and management capabilities.

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