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Analyzing the Influence Factors of New Energy Vehicles on Traditional Energy Vehicle Industry in China Based on Entropy Weighted TOPSIS and Pearson Analysis

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Abstract: With the increase of global environmental awareness and the active promotion of policies, the new energy automobile industry has gradually become a new trend in the development of the automobile industry. This study analyzes the influencing factors of the production and sales volume of new energy vehicles (EV and PHEV) and traditional fuel vehicles (OFC), and then explores the impact of new energy vehicles on the development of traditional automobile industry. The study uses 2013-2022 data to construct an entropy-weighted TOPSIS-based indicator system to quantify industry differences and identify the main influencing factors. Further, Pearson correlation analysis is used to analyze the correlation between the main indicators and production and sales volume to identify the impact of new energy vehicles on the traditional automobile industry. The results of the study reveal the significant influence of environmental and ecological indicators, economic indicators, technological development indicators and infrastructure construction on the development of new energy automobile industry. Meanwhile, the correlation between crude oil production, total energy consumption, average energy density of battery and traditional fuel vehicle industry is analyzed, which points out the impact and promotion of new energy vehicle industry on traditional automobile industry. Based on the analysis results, optimization strategies for the automobile industry are proposed to promote the sustainable development of the industry.

1. Introduction

In the context of rapid global economic development, environmental pollution and energy crisis have prompted the rapid rise of new energy vehicle industry, which has become an important choice to solve transportation and energy problems [1]. New energy vehicles are favored by the market for their clean and efficient features, which have a profound impact on the traditional fuel automobile industry, changing the preference for car purchase and promoting technological innovation and market strategy adjustment. Studies have shown that consumers' purchase intention is influenced by brand experience, perceived risk, government policy and other factors, in which brand experience has a positive effect on brand extension evaluation, and perceived risk plays an intermediary role [2], and the perception of disruptive innovation has a positive effect on the purchase intention of new energy vehicles, and has an inhibitory effect on the traditional vehicles [3].

There are significant differences between new energy vehicles and traditional fuel vehicles in terms of structure, noise, cost, infrastructure, used car market, and range [4]. China's automotive industry has achieved a strategic shift through disruptive innovation [5], which encourages new areas of development but requires policy adjustments to cope with industrial and regional differentiation [6]. Meanwhile, the cost-effectiveness of new energy vehicles replacing conventional vehicles in terms of emission reduction [7] and the long-term trend of the impact on gasoline demand in China have been studied. It is expected that new energy vehicles will completely replace conventional fuel vehicles by 2045, and China's gasoline demand will shrink after peaking in 2026 [8].

Existing studies are deficient in new energy vehicle supply chain benefits, consumer green preference, and product substitution rate [9], and most of them focus on single policy factors [10], lacking comprehensive impact analysis.

This paper constructs a comprehensive evaluation model, combines the entropy weight method and TOPSIS method, and innovatively identifies the key influencing factors of the development of new energy vehicles and traditional energy automobile industry. Pearson correlation analysis is used to explore the interaction of these factors in depth, highlighting the practicality of the construction of multi-dimensional indicator system and strategy suggestions, providing scientific basis and practical guidance for the sustainable development of the automobile industry.

2. Comprehensive evaluation model based on entropy weight method and TOPSIS

2.1 Data standardization

This paper adopts system theory to construct a comprehensive evaluation index system for new energy vehicles containing 12 secondary indicators. Due to the differences in the unit of measurement of the indicators, direct comparison is difficult. Macro-analysis shows that the indicators are divided into positive and negative effects: positive indicators indicate that the larger the value, the better the development of the system; negative indicators, on the contrary, the larger the value, the worse the development of the system.

Therefore, in order to analyse the development of different systems under the same criteria, it is first necessary to standardize the various types of indicators in the system, with the aim of eliminating the influence of the units of measurement and the positive and negative effects of the indicators. The formula for standardization is:

$$\begin{cases} \dfrac{x_{ij}-\min\limits_i(x_{ij})}{\max\limits_i(x_{ij})-\min\limits_i(x_{ij})}, & \text{Positive indicators} \\ \dfrac{\max\limits_i(x_{ij})-x_{ij}}{\max\limits_i(x_{ij})-\min\limits_i(x_{ij})}, & \text{contrarian indicators} \end{cases} \tag{1}$$

BP neural network is back propagating, mainly composed of three parts: input layer, middle layer and output layer. The number of nodes in the input and output layers is relatively easy to determine, but the determination of the number of nodes in the hidden layer is a very important and complex problem.

In the above formula, x_{ij} represents the original value of the j th tertiary indicator of the i

secondary indicator, and $x_{ij}^{'}$ is the standardized value of the item, which can be standardized by Equation 1 to obtain the standardized matrix of the indicator system:

$$X^{'} = \begin{bmatrix} x_{11}^{'} & x_{12}^{'} & \cdots & x_{1n}^{'} \\ x_{21}^{'} & x_{22}^{'} & \cdots & x_{23}^{'} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1}^{'} & x_{m2}^{'} & \cdots & x_{mn}^{'} \end{bmatrix} \tag{2}$$

2.2 Empowerment using entropy weighting

After data standardization, this paper adopts the entropy weight method to determine the weights of the indicators in order to achieve an objective and comprehensive assessment. The entropy weight method is based on the entropy value (amount of information) of each indicator to reflect its importance, avoiding the bias brought by subjective methods. Among them, the entropy value corresponding to the i th indicator in the j th period is calculated as follows:

$$H_i = -\frac{1}{\ln(n)} \sum_{j=1}^{n} p_{ij} \ln(p_{ij}) \tag{3}$$

$$p_{ij} = \frac{x_{ij}}{\sum_{j=1}^{n} x_{ij}} \tag{4}$$

Based on this, the information entropy of each indicator can be obtained as $(H_1, H_2, \ldots, H_m)$. Thus, the entropy weights of each indicator are calculated as follows:

$$w_i = \frac{1-H_i}{m-\sum_{i=1}^{m} H_i} \tag{5}$$

Suppose W is the entropy weight vector consisting of the entropy weights of each indicator, i.e., there is $W^T = (w_1, w_2, \ldots, w_m)$.

2.3 The TOPSIS model

After determining the weights of the indicators, this paper uses the TOPSIS method to calculate the system score. This method determines the ideal solution by Euclidean distance on the basis of normalization and known weights, and evaluates the proximity of each sample to the optimal solution with the formula:

$$C_i = \frac{d_i^-}{d_i^+ + d_i^-} \tag{6}$$

Where C_i denotes the closeness of the i th sample, its value is between $[0,1]$, the closer to 1 indicates that the sample scores better. According to the results of the closeness of the calculation of the samples to be sorted, you can get the final evaluation results.

2.4 Intra-factor correlation modeling

Through Pearson correlation analysis, this paper combines the key indicators with the data of new energy vehicles and traditional energy automobile industry to scientifically assess the correlation between the variables, in order to identify the main influencing factors of new energy vehicles on traditional automobile industry.

2.5 Modeling the Pearson correlation coefficient

The Pearson correlation coefficient, denoted r, measures the linear relationship between two random variables, i.e., the degree of linear association. The formula for measuring the Pearson correlation between the indicators is as follows:

$$r = \frac{\sum_{i=1}^{n}(x_i - \overline{X})(y_i - \overline{Y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{X})^2}\sqrt{\sum_{i=1}^{n}(y_i - \overline{Y})^2}} \tag{7}$$

where $\overline{X}$ and $\overline{Y}$ denote the sample means of both, respectively.

Repeat the above calculations to obtain the correlation between the indicators.

3. Results

3.1 Indicator system construction and data sources

3.1.1 Construction of the indicator system

The comprehensive assessment index system for new energy vehicles contains four primary indicators and 12 secondary indicators. Among them, the secondary indicators reflecting policy influence (P) include three: general public budget expenditure ($GPBE$), estimated value of government subsidies (EGS), and the number of charging piles ($NCPL$), which are all positive indicators; the secondary indicators reflecting technology research and development (T) include three: total power generation (TPG), average energy density of batteries ($ABED$), and the number of charging piles (NCP), which are all positive indicators; the secondary indicators reflecting economic development (E) include three: per capita GDP per capita (GDP), the total amount of import and export ($TIBV$), and the index of new driving force for economic development ($NGDI$), all positive indicators; the secondary indicators reflecting the environment and ecology (M) include three: total energy consumption (TEC), crude oil production (GOP), and carbon dioxide emissions (CO_2E), all negative indicators. The specific indicator system is shown in Table 1.

Table 1: Comprehensive assessment index system for new energy vehicles

Level 1 indicators	Secondary indicators	work unit	Indicator properties
Policy implications (P)	General public budget expenditure ($GPBE$)	Billions	+
	Estimates of government subsidies (EGS)	Million dollars/vehicle	+
	Number of charging piles laid	Ten thousand	+

	($NCPL$)	units	
Technology development (T)	Total power generation (TPG)	kWh	+
	Average battery energy density ($ABED$)	Wh/kg	+
	Number of charging piles (NCP)	Ten thousand units	+
Economic development (E)	Gross Domestic Product (GDP)	Ten thousand dollars	+
	Total import and export value ($TIBV$)	Trillion dollars	+
	New growth drivers Index ($NGDI$)	Billions	+
Environmental ecology (M)	Total energy consumption (TEC)	Tons of standard coal	-
	Crude oil production (GOP)	Billion tons	-
	Carbon dioxide emissions (CO_2E)	Million tons	-

3.1.2 Data sources

This topic analyzes the development of new energy and its influencing factors by selecting data from the Department of Energy Statistics, China Urban Statistical Yearbook, Classification of Strategic Emerging Industries, and New Energy Vehicle Production and Sales Profile 2013 - 2022 respectively. Relevant data were obtained from the official website of China Statistics Bureau, China Association of Automobile Manufacturers, and Energy Research Institute. Missing data for individual years are obtained by interpolation and trend extrapolation.

3.2 Analysis of experimental results

According to the indicator evaluation system established by the entropy-weighted TOPSIS model, we obtained the values of the weights of the indicators and the comprehensive scores for each year in the context of the development of the new energy industry calculated by the model as shown in Table 2:

According to the results of the above table, carbon dioxide emissions, the number of charging piles, the new momentum index of economic development, the number of charging piles, the total amount of imports and exports, and the average energy density of batteries for the new energy automobile industry and the traditional automobile industry, the weight ranking of the top six influencing factors indicators. At the same time, it can be inferred that the development trend of environment, economy, science and technology, and government indicators have different sizes of influence on the object of study, which also indicates that the rise and fall of the automobile industry has a close relationship with the development of all aspects, especially in environmental protection and energy economy is particularly important. Specific calculations are shown in Table 3.

Table 2: Calculation table for weights of rating indicators

Evaluation indicators	Information entropy H_i	information utility value d	Weights W_i
General public budget expenditure	0.931	0.069	3.162
Estimated value of government subsidies	0.882	0.118	5.398
Number of charging piles laid	0.758	0.242	11.026
China's total power generation	0.86	0.14	6.402
Average battery energy density	0.839	0.161	7.353
Charging pile ownership	0.788	0.212	9.681
GDP per capita	0.867	0.133	6.082
Total exports and imports	0.801	0.199	9.068
Index of new dynamics of economic development	0.764	0.236	10.781
Total energy consumption	0.906	0.094	4.288
Crude oil production	0.898	0.102	4.668
Carbon dioxide emissions	0.516	0.484	22.09

Table 3: Calculation table for rating indicator scores by year

Particular year	Positive ideal solution distance(D+)	Negative ideal solution distance(D-)	Aggregate score	Arrange in order
2013	0.82931244	0.51920943	0.38502114	5
2014	0.89658241	0.22049876	0.1973883	9
2015	0.90305912	0.20600211	0.18574458	10
2016	0.83972627	0.29741724	0.26154767	8
2017	0.77496138	0.39651414	0.33847412	7
2018	0.70917828	0.43766147	0.38162391	6
2019	0.65603259	0.4602142	0.41228714	4
2020	0.59861205	0.50559057	0.45787844	3
2021	0.53764138	0.65780355	0.55025834	2
2022	0.55023821	0.80352371	0.59354876	1

After calculating the correlation coefficient through Pearson, we scientifically and objectively analyze that the main influencing factors and relationships of new energy vehicles on traditional energy automobile industry are shown in Figure 1.

Heat map analysis shows that sales of conventional fuel vehicles are positively correlated with crude oil production and their own production, as well as negatively correlated with energy consumption, battery energy density and public budget spending, and with GDP per capita and the number of charging piles. Production is similarly affected by the positive correlation between crude oil production and sales, as well as the negative correlation between public budgets, charging piles and battery energy density, and by total electricity generation and the New Dynamic Energy Index of Economic Development. This suggests that the rise of the new energy automobile industry is impacting the traditional automobile industry and driving its transformation and upgrading.

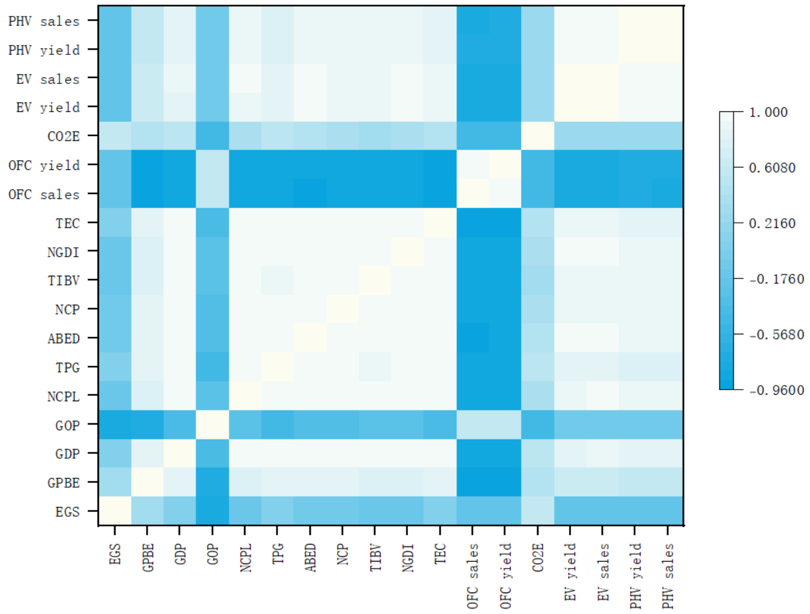

Figure 1: Heat map of Pearson's correlation coefficient

4. Conclusions

This study comprehensively applied the entropy weight method, TOPSIS model and Pearson correlation analysis to systematically assess the influencing factors of China's new energy vehicle and traditional energy vehicle industries. Through the analysis of data from 2013 to 2022, key indicators were identified and their impact on industry development was quantified. The results show that environmental and ecological indicators (e.g., carbon dioxide emissions) and economic indicators (e.g., total imports and exports and new momentum index for economic development) have a significant positive impact on the new energy vehicle industry. Technological development (battery energy density) and infrastructure (number of charging piles) are also key to driving industry development. The TOPSIS model assessment shows that the new energy vehicle industry scores the highest in 2022, suggesting that the industry is in an ideal situation related to policy support, technological advancement, and market demand growth.

Pearson analysis reveals the complex relationship between the new energy automobile industry and the traditional automobile industry, the positive correlation between the production of crude oil and the production of fuel automobiles, as well as the negative correlation between the total energy consumption and the energy density of batteries, which verifies the impact of the new energy automobile industry on the traditional industry.

It is suggested that the government should strengthen the support of new energy automobile industry, especially in technology research and development and infrastructure construction. Automakers should increase technological innovation to adapt to market and consumer demand. Future research could explore the combined impact of policy combinations and the promotion of traditional industry transformation. This study provides a new perspective for understanding industrial interactions, provides a scientific basis for policy formulation and industrial development strategies, and is of great significance for promoting the sustainable development of the automobile industry.

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