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Development Stages and Evolutionary Trends of China's Energy Competitiveness

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Abstract

Energy competitiveness is a quantitative indicator used to assess the comprehensive strength and development potential of a country or region in the energy sector. Currently, most existing research on China's energy development has focused on single-dimensional aspects such as energy intensity and resilience. Meanwhile, few studies have comprehensively analysed the development foundation and trends of China's energy sector from a competitiveness perspective. In the study, energy competitiveness is defined in terms of four aspects: resource endowments, industrial structure, related industry development, and demand conditions. The objective entropy weight method is employed to quantitatively measure China's energy competitiveness from 1980 to 2020. An in-depth analysis of its development process and influencing factors is subsequently conducted. Results show that, (1) China's energy competitiveness exhibits an overall upward trend. According to its distribution characteristics, it is categorized into three historical stages: the "slow growth period," the "plateau period," and the "rapid expansion period"; (2) In the development of China's energy competitiveness, factors such as technological progress, residents' traditional lifestyles, energy production, and residents' new forms of consumption exert relatively large marginal impacts; (3) The importance of each key influencing factor varies across different stages, which results in distinct temporal variation patterns and nonlinear response relationships. The proposed measurement model of China's energy competitiveness is feasible. The obtained conclusions provide a significant reference for effectively promoting sustainable energy development in the country.

Keywords: Energy competitiveness, Comprehensive evaluation, Random forest, Entropy weight method

1. Introduction

Energy is a fundamental material basis for human existence and development. At present, the global energy landscape is profoundly and unprecedentedly changing [1]. The rapid advancement of science and technology has enabled the development of new energy technologies and increased the proportion of clean energy, such as solar, wind, hydropower, and nuclear energy [2]. Fossil fuel reserves are steadily declining, while extraction costs continue to rise. The international energy market remains highly volatile, while geopolitical factors exert an increasing influence on energy supply and prices. Consequently, countries are actively seeking effective strategies to strengthen their energy competitiveness [3]. China, as the world's largest developing nation, holds a pivotal position in the global energy landscape. In recent years, China's rapid economic growth has led to a sustained increase in energy demand, which makes it the world's largest energy consumer [4]. The International Energy Agency [5] reported that China's installed renewable energy capacity rose from 35% in 2015 to 48% in 2023. However, China's energy resource endowment is characterized by an abundance of coal, a scarcity of oil, and limited natural gas reserves. The country has highly relied on imported oil and natural gas for a long time. In 2024, China's dependence on imported oil has already exceeded 70%. This situation renders China's energy system continues to grapple with the "impossible triangle" challenge [6]. And the country's energy supply highly susceptible to fluctuations in the international market, which creates significant challenges for its energy security.

In this context, conducting a comprehensive analysis of China's energy competitiveness and identifying its key constraints are crucial for strengthening the country's energy competitive advantage and advancing sustainable energy development. Unfortunately, existing research primarily focuses on single-dimensional and single-factor analyses of energy efficiency and security [7-9]. This single-dimensional analytical framework cannot consider the complexity of the energy system and does not adequately capture the mechanisms driving the formation of a country or region's energy system competitive advantage.

Fortunately, competitiveness theory offers new insights for a comprehensive understanding of the advantages and disadvantages of a country or region in the energy sector. Competitiveness theory provides a structured framework for researching China's energy development, which facilitates a transition from a single-dimensional economic efficiency analysis to a comprehensive multidimensional system evaluation by systematically examining the endogenous drivers of industrial competitiveness. Compared with traditional single-dimensional analyses, energy competitiveness theory exhibits distinct advantages through its emphasis on factor integration and dynamic adaptability [10]. Currently, several scholars have conducted exploratory research on corporate energy competitiveness, which confirms that the quantitative evaluation of competitiveness in the energy sector is feasible and important. Sadorsky [11]

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used a dynamic panel model and demonstrated that a 1 percentage point increase in corporate energy competitiveness in industries with high energy consumption causally leads to a 0.3–0.5 percentage point increase in total factor productivity. This relationship is significantly moderated by institutional quality. However, few studies have focused on the competitiveness of the energy industry, and no scholar has examined the macro and micro factors that play a critical role in shaping China's energy competitiveness. Thus, this study endeavors to construct a comprehensive evaluation model of China's energy competitiveness based on competitiveness theory. It employs the objective entropy weight method to address the following research questions:

(1) What is the current status of China's energy competitiveness, and what stages has its development and evolution undergone?

(2) What are the primary constraints on China's energy competitiveness?

(3) How do different factors influence China's energy competitiveness across various stages of development?

The study primarily contributes in the following aspects. First, the entropy weight method was employed to construct a comprehensive evaluation model of China's energy competitiveness. This model enables a quantitative analysis of its competitive advantages and disadvantages while addressing the limitations of overly narrow research perspectives. Second, the random forest model was introduced and optimized to identify key factors influencing China's energy competitiveness. The nonlinear marginal impacts of various factors at different development stages were analyzed, which provides a quantitative basis for policy formulation.

The rest of the study is structured as follows. Section 2 elaborates the research design. Section 3 details the model construction process. Section 4 provides an in-depth analysis of China's energy competitiveness measurement results, with systematic explanation of its overall status, key influencing factors, and the marginal effects of different factors. Section 5 concludes with a summary and the key research findings.

2. Literature review

Previous studies on energy development levels have mostly focused on a single-factor perspective. For example, many studies have measured regional or national energy development levels using a single indicator, such as energy intensity, per capita energy consumption, or the proportion of renewable energy [12-13]. Although this type of research can simplify the analysis process and quickly identify shortcomings in specific dimensions, it is difficult to fully describe the complex correlations and dynamic evolution of multiple factors within the energy system [14]. For example, early literature often evaluated energy endowment advantages based on the linear logic of "resources-production-consumption", but ignored the role of technological innovation in reconstructing resource utilization efficiency. Alternatively, it measured the level of energy decarbonization solely by total carbon emissions, without fully considering the impact of offsetting mechanisms such as carbon sink capacity and carbon trading market maturity. The traditional evaluation system, which is centered on "energy intensity", is increasingly considered insufficient to account for the complex impact of emerging technologies, geopolitics, and climate policies in shaping competitiveness. Therefore, developing an integrated analytical framework is urgently needed [15]. At the thematic level, the concept of energy competitiveness, which emphasizes the coordinated optimization of multiple energy development objectives, has gradually gained widespread attention from scholars. Competitiveness theory provides a multidimensional analytical framework for energy system research by systematically deconstructing the dynamic relationships among factor endowments, industrial structure, and the institutional environment of economic entities [16]. In 1990, Porter proposed a competitiveness framework that marked a shift from absolute advantage and comparative advantage to competitive advantage. Competitiveness theory emphasizes that the economic prosperity or decline of a country or region depends on its ability to establish a competitive advantage. The key to achieving industrial competitiveness depends on the integration of four fundamental factors: resource endowments, industrial structure, related industry development, and demand conditions. Energy competitiveness, as an indicator of a country or region's overall strength in the energy sector, involves various dimensions, including energy resource endowment and energy utilization efficiency. At the methodological level, with the rise of systems theory, scholars have gradually shifted from single-factor analysis methods, such as data envelopment analysis (DEA), to constructing multidimensional indicator systems to better capture the complexity of energy development. McClelland was the first to combine DEA with the directional distance function to quantify the impact of environmental constraints on the energy efficiency of coal-fired power plants in the United States [17]. Although Ang's Laspeyres index decomposition method effectively identifies the driving factors of industrial energy efficiency, it reduces the energy system to a closed technical-economic model [18]. Thus, this method fails to account for exogenous shocks in energy security and other critical dimensions. Gnansounou's energy vulnerability index integrates 11 technical and economic indicators. It reveals a time-lag deviation of 3 to 5 years in its response to changes in renewable energy penetration, as indicated by sensitivity analysis [19]. The International Energy Agency quantified the distribution of the global population without electricity through the Multidimensional Poverty Index [20]. However, this approach reduces energy infrastructure investment to a linear cost function and fails to consider the role of community participation and socio-cultural factors. While the "Beyond Connections" framework proposed by Batidzirai et al. [21] incorporated service quality indicators, it failed to establish a quantitative correlation model with energy efficiency improvements.

In general, the comprehensive evaluation method not only overcomes the fragmentation issues of the single-factor perspective through system integration, dynamic feedback, and heterogeneous deconstruction but also serves as a core analytical tool for addressing the energy "impossible triangle" (safety, economy, and low carbon). Furthermore, it provides a scientific benchmark for strategic path selection in the global carbon neutrality process [22]. In comprehensive evaluation modeling, methods such as principal component analysis (PCA), the entropy method, and the analytic hierarchy process (AHP) are widely used for indicator dimension reduction and weight allocation [19]. PCA extracts the main factors of competitiveness by maximizing variance, as seen in the EU energy triangle model [23]. The AHP relies on expert scoring and is easy to implement, but it is prone to introducing cognitive biases. Pohekar [24] constructed an AHP framework with 12 core indicators, such as energy cost, carbon emission intensity, job creation potential, and technological maturity. The weights were determined, and the comprehensive score was calculated using expert questionnaires. The entropy weight method is based on data characteristics, objectively assigns weights using information entropy, avoids subjective bias, and enables the automatic weighting of multidimensional data. Lin and Wesseh [25] selected 12 indicators from the dimensions of energy consumption, economic output, and environmental pressure and determined their objective weights using the entropy weight method. Budzianowski and Postawa [26] effectively combined the entropy weight method with grey correlation analysis and selected 18 indicators from four subsystems: energy supply, economic cost, environmental constraints, and technological resilience. He then constructed a comprehensive evaluation system for national energy security and identified key risk factors. In comparison, the entropy weight method is more objective, effectively handles the problem of multi-index collinearity, and is suitable for evaluating complex systems.

Therefore, considering the limitations of previous studies, the objective entropy weight method is employed to quantitatively assess China's energy competitiveness from 1980 to 2020. In addition, the random forest algorithm is utilized to conduct an in-depth analysis of its development process and key influencing factors.

3. Methodology

3.1 Analysis of the connotation of energy competitiveness

Competitiveness is a multidimensional dynamic concept that refers to the ability of an individual, organization, industry, or country to effectively allocate resources, continuously innovate, and respond to challenges in a specific environment. This dynamic concept allows them to gain advantages in competition and achieve long-term sustainable development. Competitiveness theory emphasizes that innovation is the core driving force for improving competitiveness. The input of innovation factors can be measured by expenditure on research and experimental development in the energy industry. Research and experimental development expenditures are the material basis for innovation in the energy field, and sufficient funds can promote the transformation of energy technology [27].

Industrial structure is an important indicator of competitiveness. Energy intensity, as a key indicator to measure the rationality of industrial structure, reflects the coupling relationship between energy and economic development. Lower energy intensity suggests that economic development is less dependent on energy, and more economic output can be obtained with less energy inputs. This lower dependency on energy enhances the overall competitiveness of the economy and thus strengthens the supporting role of energy in economic development and its own competitiveness [28].

The development of related industries has an important supporting and driving role in the competitiveness of core industries. The proportion of installed capacity for clean energy power generation is an important indicator reflecting the development of related industries. An increase in the proportion of installed capacity for clean energy power generation signifies the growth of the clean energy industry itself. It also facilitates the development of related industries, including energy storage, smart grids, and energy services [29].

Demand condition is an important factor influencing competitiveness. External dependence of energy is a direct indicator of demand conditions. Lower external dependence of energy indicates that a country or region can fulfill most of its energy needs using its own energy resources. This ability to meet energy needs reflects a fundamental requirement and a key aspect of energy competitiveness [30].

Therefore, enhancing China's energy competitiveness must be based on the country's energy resource endowments. Notably, ensuring energy security and meeting the needs of economic and social development are fundamental prerequisites. The focus should be on clean and low-carbon transition, which is driven by technological innovation. The aim is to meet the people's energy needs for a better life and promote the construction of a clean and beautiful world.

3.2 Research methods

(1) Comprehensive evaluation model. In this study, the entropy weight method is used to comprehensively evaluate China's energy competitiveness level during the period of 1980–2020. The entropy weight method, as an approach for analyzing objectively weighted data commonly used in economics, overcomes the problem of subjectivity of artificial weighting. It has better objectivity and accuracy to explain the obtained results than the subjective weighting method [31-32].

According to the "14th Five-Year Plan" for energy and existing research [33-36], the comprehensive score of China's energy competitiveness level from 1980 to 2020 was calculated using the entropy weight method based on the indicator system shown in Table 1. The specific calculation steps are as follows.

Table 1. Composition of China's energy competitiveness indicators

Primary indicator	Secondary indicator	Unit	Characterization
Innovation element	R&D expenditure	100 million yuan	Positive effect
Industrial structure	Energy intensity	tons of SCE/10,000 yuan	Negative effect
Development of related industries	Proportion of installed capacity for clean energy power generation	%	Positive effect
Demand condition	External dependence of energy	%	Negative effect

In the first step, the indicators are standardized using the extreme value method to address the variability of the different indicators. According to the different characteristics of the indicators, the positive and negative indicators are treated using Formula (1):

$$z_{ij} = \frac{x_{ij} - \min X_j}{\max X_j - \min X_j}, zi_j = \frac{\max X_j - x_{ij}}{\max X_j - \min X_j} \quad (1)$$
$$(i = 1, 2, \cdots, n; j = 1, 2, \cdots, m)$$

In the second step, the entropy value E_j is calculated as:

$$Ej = -\ln\frac{1}{n}\sum_{i=1}^{n}[(Z_{ij}\Big/\sum_{i=1}^{n}Z_{ij})\ln(Z_{ij}\Big/\sum_{i=1}^{n}Z_{ij})] \tag{2}$$

In the third step, the difference coefficient D_j is calculated as:

$$D_j = 1 - E_j \tag{3}$$

In the fourth step, the weights of each indicator are calculated as:

$$W_j = \frac{D_j}{\sum_{j=1}^{n} D_i} \tag{4}$$

The fifth step involves calculating the comprehensive score of China's energy competitiveness. After the entropy weighting method is applied to calculate the comprehensive weights of each indicator, the comprehensive score for each year is calculated using Formula (5):

$$G_j = \sum(W_i Y_{ij}) \tag{5}$$

where G_j denotes the composite energy competitiveness score in year j; W_i denotes the combined weight of the ith indicator; Y_{ij} denotes the value of the ith indicator in year j; $i=1,2,\cdots,n; j=1,2,\cdots,m$.

(2) Random forest model. Random forest is a (parallel) integration algorithm composed of decision trees. It belongs to the Bagging type. By combining multiple weak classifiers, the final result is voted or averaged. As a result, the results of the overall model have high accuracy and generalization performance. It is widely used in various business scenarios because of its good stability [37]. Compared with a single decision tree, random forest can effectively reduce the risk of overfitting and improve the stability and generalization performance of the model. In addition, random forest can handle missing data with high adaptability and robustness, which makes it a powerful machine learning model. In this study, the random forest method is used to identify the key influencing factors.

(3) Forecast error. Suitable indicators need to be used to measure the prediction errors of random forests for assessing their prediction accuracy. Mean squared error (MSE) is a commonly used assessment indicator to measure the difference between predicted and actual values. It is the square of the average of all prediction errors, which has good mathematical properties and is easy to interpret. In random forests, MSE can be used as an effective evaluation indicator for comparing the prediction accuracy under different parameter configurations. By cross-validating and tuning the random forest, its prediction accuracy can be further improved, and the performance of MSE indicator can be optimized. Therefore, the MSE indicator is used in this study to assess the accuracy of the random forest model:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(observed_i - predicted)^2 \tag{6}$$

where $observed_i$ is the true value, *predicted* is the predicted value, and N is the number of samples. The *MSE* indicator can be used to evaluate the accuracy of the prediction model. A smaller MSE value means higher accuracy of the model.

3.3 Data sources

The research scope defined by this study is China's energy competitiveness and related impact factor indicator data from 1980 to 2020. These data comprise important economic data, social data, energy data, and environmental development data from China in the past 40 years, with a total of 69 detailed indicators. The relevant data come from various sources, such as China Statistical Yearbook, China Industrial Statistical Yearbook, China Energy Statistical Yearbook, China Trade Union Statistical Yearbook, and China High-Tech Industry Statistical Yearbook. Public data of the National Bureau of Statistics and the IEA database for corresponding years are also used. Missing values in some data are interpolated.

In terms of the selection of potential influencing factors, this study refers to the existing research [38-40] and considers data availability and relevance. A total of 69 indicators are selected to comprehensively describe the influencing factors of China's energy competitiveness from 1980 to 2020 (Table 2). According to the relevance of the indicators and their specific meanings, these factors are categorized into nine categories: energy consumption, energy production, fossil energy prices, non-fossil energy power generation, residents' traditional lifestyles, size of industries with high energy consumption, technological progress, residents' new forms of consumption, and share of the service sector.

Table 2. Indicator system of factors influencing energy competitiveness

Category	Factor indicators
Composition and proportion of energy consumption	Proportion of raw coal consumption Proportion of crude oil consumption Proportion of natural gas consumption Proportion of hydropower consumption Proportion of nuclear power consumption
Fossil energy prices	Producer price index for coal industry Producer price index for petroleum and natural gas industry
Proportion of non-fossil energy power generation	Proportion of thermal power generation Proportion of hydropower generation Proportion of nuclear power generation Proportion of wind power generation Proportion of solar power generation
Proportion of service industry	Proportion of financial industry Proportion of information transmission, computer services, and software industry Proportion of education industry

	Proportion of health, social security, and social welfare industry Proportion of culture, sports, and entertainment industry Proportion of scientific research, technical services, and geological exploration industry
Residents' traditional lifestyles	Per capita disposable income of urban residents Per capita disposable income of rural residents Number of civilian vehicles owned Total supply of artificial gas in urban areas Population using artificial gas in urban areas Total supply of natural gas in urban areas Population using natural gas in urban areas Total supply of liquefied petroleum gas in urban areas Population using liquefied petroleum gas in urban areas Number of private cars per 100 urban households Number of motorcycles per 100 urban households Number of motorcycles per 100 rural households Number of refrigerators per 100 urban households Number of refrigerators per 100 rural households Number of television sets per 100 urban households Number of television sets per 100 rural households Number of washing machines per 100 urban households Number of washing machines per 100 rural households
Scale and proportion of industries with high energy consumption	Industrial scale of soda ash Industrial scale of caustic soda Industrial scale of ethylene Industrial scale of synthetic ammonia Industrial scale of cement Industrial scale of flat glass Industrial scale of crude steel Industrial scale of finished steel Proportion of construction industry Proportion of transport, storage, and postal services
Technological progress	Overall labor productivity Processing and conversion efficiency of power generation and station heating Processing and conversion efficiency of coking Processing and conversion efficiency of oil refining Standard coal consumption for power generation Standard coal consumption for power supply Line loss rate of power plants Comprehensive energy consumption per unit in the crude steel industry Comprehensive energy consumption per unit in the cement industry Comprehensive energy consumption per unit in the ethylene industry Comprehensive energy consumption per unit in the synthetic ammonia industry Proportion of science and technology appropriation in total fiscal expenditure
Residents' new forms of consumption	Internet broadband subscribers High-speed railway operating mileage Railway operating mileage E-commerce transaction volume New energy vehicle sales Mobile phone penetration rate
Composition and proportion of energy production	Proportion of raw coal production Proportion of crude oil production Proportion of natural gas production Proportion of hydropower production Proportion of nuclear power production

4. Model Establishment

4.1 Model selection

The variables in the dataset collected for this study have no linear relationship. Thus, a regression model is chosen for the prediction model. By comparing the MSE indicator of model accuracy, the regression algorithm with the smallest MSE is used to establish a predictive model. Different regression algorithms are suitable for different types of data, and appropriate algorithms can be applied for prediction based on the characteristics and needs of the data. The dataset in this study contains a large number of features. The relationships among these features are complex and cannot be easily described by a simple linear model. Therefore, this study uses three methods widely used in nonlinear relationship analysis, namely, random forest regression, support vector machine, and decision tree regression algorithm. The performance of the three methods is compared (Table 3).

Table 3. Three types of common regression models

Algorithm	Features
Decision tree regression	By recursively partitioning the dataset, a decision tree is built, which is suitable for continuous and discrete data. The decision tree algorithm can automatically perform feature selection but is prone to overfitting.
Support vector regression	Regression is performed by finding the optimal hyperplane, which is suitable for high-dimensional and nonlinear data. This algorithm can effectively handle small sample problems but requires longer training time for large sample data.
Random forest regression	An ensemble learning method that builds multiple decision trees for regression is established, which is suitable for continuous and discrete data. The random forest algorithm can reduce the risk of overfitting but needs careful parameter tuning.

In this study, the dataset is first divided into a training set and a test set. The training set is used for model training, while the test set is utilized to evaluate the predictive performance of the model. In the process of model performance evaluation, MSE is adopted as a measure to assess the prediction accuracy of the model. A lower MSE value indicates that the deviation between the prediction result and the actual value of the model is smaller, which suggests that the prediction accuracy of the model is higher.

The results show that the random forest regression algorithm has the smallest MSE value, which is 0.00047 (Fig. 1). By contrast, the MSE indicators of support vector machine and decision tree regression are 0.00052 and 0.0059, respectively. Therefore, this study selects the random forest regression algorithm with the smallest MSE for model prediction.

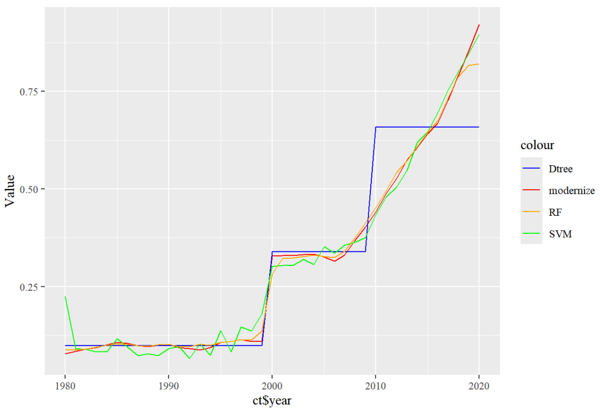

Fig. 1. Comparison of prediction performance of random forest, support vector machine, and decision tree models

4.2 Parameter tuning
Random forest models are widely used in machine learning due to their excellent fitting capabilities. However, higher model complexity leads to an imbalance in the bias–variance trade-off, as evidenced by lower model bias accompanied by higher estimated variance. The complexity of a model needs to be constrained by a systematic hyperparameter optimization strategy to improve its generalization performance. This study adopts a hybrid method based on cross-validation-based grid search (GridSearchCV) and manual parameter optimization. This method focuses on two core hyperparameters in the random forest algorithm—“mtry” (number of candidate features during node splitting) and “ntree” (number of decision trees) are tuned.

The tuning process adopts a grid search strategy to achieve parameter tuning by iteratively adjusting the “ntree” value and evaluating the performance of the model on the test set based on selected performance indicators (e.g., mean square error or R^2). The results are shown in Fig. 2 and Fig. 3.

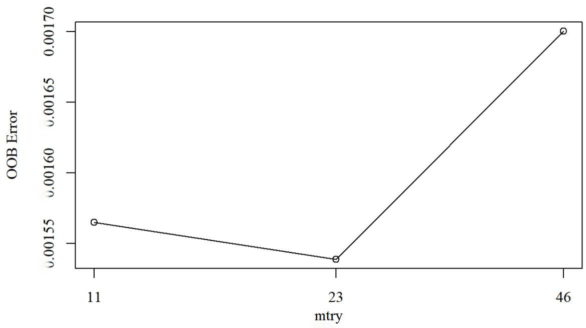

Fig. 2. Optimization of the number of mtry

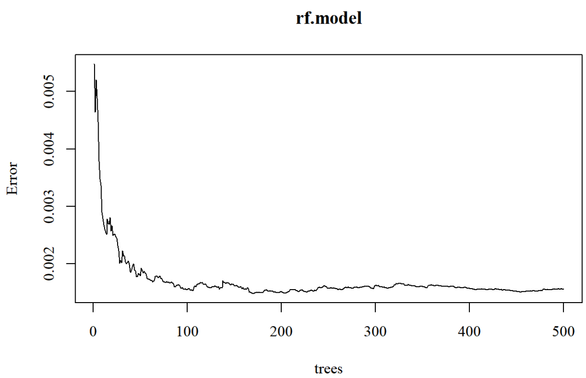

Fig. 3. Modeling error rate for different ntree

4.3 Particle update rules
Random forest regression modeling is an effective forecasting method, but its predictive performance is significantly affected by the influencing factors. This study proposes an optimal influence factor selection method based on cross-validation curve analysis to improve the prediction accuracy of random forest regression models. Cross-validation evaluates model performance by dividing the training and validation sets multiple times and plotting cross-validation curves to visualize the relationship between model error and the number of influence factors used for fitting. By analyzing the cross-validation curves, this study determines that 14–20 significant influences need to be retained to obtain optimal regression results. As the number

of influencing factors increases, the model error shows a tendency of decreasing and then stabilizing or even increasing. Therefore, based on the trend of the curve, a range of the number of influencing factors is chosen to minimize the errors (Fig. 4).

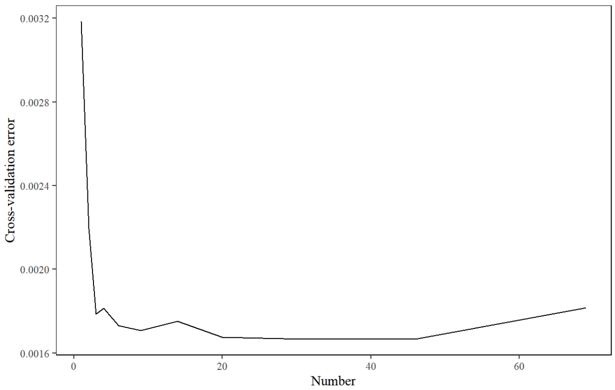

Fig. 4. Number of significant variables identified by cross-validation

5. Results analysis

5.1 China's energy competitiveness in general

In this study, the entropy weight method is used to measure China's energy competitiveness level from 1980 to 2020, and the results are shown in Fig. 5. The results show that China's energy competitiveness level exhibits a continuous upward trend. The level increases from 0.0779 in 1980 to 0.9229 in 2020, which is a rise of 1084.72%. Further analysis reveals that the development of China's energy competitiveness level can be divided into three phases: the slow-growth period of 1980–1999, the plateau period of 2000–2007, and the rapid expansion period of 2008–2020. Analyzing the influencing factors of energy competitiveness level in each period is important in exploring the path of energy competitiveness enhancement with Chinese characteristics.

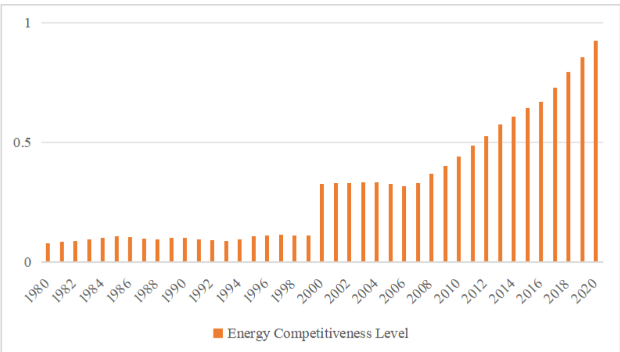

Fig. 5. Energy competitiveness level in China from 1980 to 2020

5.2 Identification of key influential factors for China's energy competitiveness

In this study, the dataset is divided into a training set and a test set to support the construction of the model and the subsequent parameter optimization. This process is conducted by normalizing the data of potential influencing factors within the year. Then, the influencing factors are split into a training set and a testing set. The variable importance index based on the Gini coefficient (IncMSE) and the node purity (IncNodePurity) is used to determine the degree of contribution of the influencing factors to the energy competitiveness indexes of the year and rank them. A larger value for both indicates greater importance to the energy competitiveness variables. Furthermore, the partial dependence plots of the variables are plotted using the partialPlot function to visualize the marginal effect of each influencing factor on the model output.

From the output results shown in Fig. 6 and Fig.7, the variable importance index (IncMSE) and node purity (IncNodePurity) are similarly sorted. The influencing factors with high importance ranking for the variable importance index (IncMSE) are shown in Fig. 8. Among them, the standard coal consumption of power generation, the line loss rate of power plants, the number of private cars per 100 urban households, the standard coal consumption of power supply, the proportion of crude oil production, the processing and conversion efficiency of power generation and station heating, the total supply of natural gas in urban areas, and the number of Internet broadband subscribers are classified into categories such as technological progress, residents' traditional lifestyles, energy consumption, residents' new forms of consumption, and energy production. Their importance in energy competitiveness indicators exceeds 5%. This finding suggests that the abovementioned indicators have played a significant role in improving energy competitiveness over the past 40 years of development. Therefore, these key factors should receive special attention in future energy development strategies compared with other indicators of lesser importance. Targeted implementation of policies such as promoting energy technology innovation and improving energy efficiency can be considered to more effectively promote the improvement in energy efficiency levels, build a modern energy system, promote high-quality energy development in the new era, and thus achieve modern transformation in the energy field. Further analysis reveals differences in the impact of consumption and income indicators of urban and rural residents on energy competitiveness. Notably, the impact of urban residents' energy consumption in traditional lifestyles on energy competitiveness is significantly higher than that of rural residents. The differences in energy consumption patterns between urban and rural areas may be related to the significant variations in economic levels, cultural levels, and lifestyles between urban and rural residents. Therefore, in the process of deepening the construction of new urbanization, the government should consider the differences in the impact of urban and rural residents' income and consumption on energy intensity. Targeted relevant energy conservation and emission reduction policies should be formulated and implemented based on this aspect.

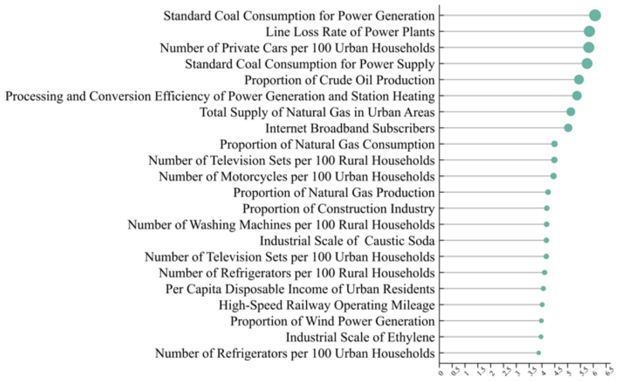

Fig. 6. Ranking of energy competitiveness impact factors from 1980 to 2020 (IncMSE)

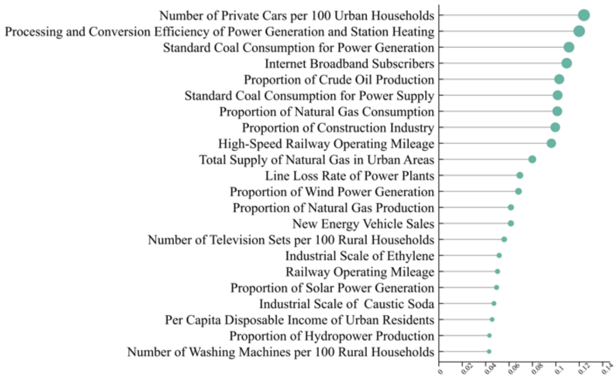

Fig. 7. Ranking of energy competitiveness impact factors from 1980 to 2020 (IncNodePurity)

5.3 Analysis of the marginal role of key factors

5.3.1 Marginal impact of key factors

The impact of standard coal consumption for power generation on energy competitiveness shows a stepwise decreasing trend. On the contrary, the level of energy competitiveness jumps in a stepwise manner as the standard coal consumption for power generation is gradually reduced (Fig. 8a). The impact of the processing and conversion efficiency of power generation and station heating on energy competitiveness shows a stepwise increase and stabilizes around 44% (Fig. 8b). This result suggests a threshold effect of technological progress on energy competitiveness. Moreover, technological innovation and upgrading to some extent will promote the reduction in pollution and energy emissions for a certain period of time. As a result, the gradual increase in the level of energy competitiveness will be promoted.

The impact of the number of private cars per hundred households in urban areas on energy competitiveness initially shows a rapid increase, followed by a gradual slowdown. It reaches an inflection point at approximately 22 cars per hundred households. Beyond this point, the degree of influence slowly rises (Fig. 8c). According to the “Blue Book of Automotive Society” released by the Institute of the Chinese Academy of Social Sciences, the number of private cars per hundred households in China exceeded 20 in 2012, which signifies that China has officially entered the era of an automobile society. Furthermore, this figure continues to rise steadily. Automobiles, as a big-ticket item, have a massive consumption scale. Thus, they not only directly drive demands for the automotive manufacturing industry but also stimulate consumption in related sectors such as steel, which raises concerns on energy consumption. Therefore, as incomes rise, residents’ demands and expectations for consumption will continue to increase. In implementing a strategy that prioritizes conservation, the promotion and education of resource-efficient consumption patterns among the public should be strengthened. With regard to automobile consumption, efforts should be made to actively guide private consumers in adopting the low-carbon travel concept associated with new energy vehicles. At the same time, developing alternative fuel vehicles and next-generation automotive energy propulsion systems is greatly important for achieving China’s energy conservation priorities and the sustainable development of the automotive industry.

The impact of the proportion of natural gas production on energy competitiveness slightly declines first and then flattens up, followed by a rapid increase. After the proportion of natural gas production reaches 6.5%, the impact still presents an upward trend, but the growth rate slows down (Fig. 8d). This result indicates that the development of renewable energy still encounters numerous challenges within the current energy production structure. Natural gas, as a low-carbon energy source among fossil fuels, is playing an increasingly important role in ensuring China’s energy supply and security, as well as optimizing the energy structure. Therefore, the existing issues in the development and utilization of clean resources such as natural gas in China need to be addressed. The sustained positive contribution of natural gas and other clean energy sources to energy competitiveness can be effectively realized by thoroughly analyzing and resolving these problems.

The impact of Internet broadband subscribers on energy competitiveness is increasing, and their number has stabilized at around 730 million households (Fig. 8e). The impact of high-speed railway operating mileage on energy competitiveness also exhibits an upward trend, which stabilizes after reaching 7,621 km (Fig. 8f). This trend indicates that, since entering the era of electrification, on the one hand, the widespread adoption and effective application of the Internet have facilitated deep integration with various industries, which enables more efficient utilization of social public resources and energy. On the other hand, the electrification of high-speed railways, which is characterized by “converting oil to electricity,” helps optimize the energy consumption structure of the railway system. This optimization drives energy conservation and emission reduction efforts.

The impact of the proportion of natural gas consumption on energy competitiveness initially remains at a low and stable level. However, the impact level increases rapidly after the threshold of 3% is reached. Finally, after the proportion reaches 4.2%, it shows a steady upward trend (Fig. 8g). Compared with the global energy structure, China’s energy consumption structure is severely imbalanced. Specifically, coal remains the dominant source, while various natural gas consumption indicators stay at relatively low levels. Therefore, increasing the proportion of natural gas, nuclear power, and other renewable energy in energy consumption is necessary to adjust the energy consumption structure. This adjustment is vital for reducing coal consumption and carbon dioxide emissions, which achieves the low-carbon development goals of energy.

The impact of the proportion of construction industry on energy competitiveness initially remains at a low and stable level. When the threshold of 6.3% is exceeded, the degree of impact increases rapidly. Eventually, a stable trend emerges after the proportion reaches 7% (Fig. 8h). The reason is that China’s construction industry has promoted industrial upgrading and low-carbon development in recent years. The electrification process of the construction industry is fast, among which electricity consumption gradually replaces coal consumption. The data provided by the National Bureau of Statistics of China and the International Renewable Energy Agency showed that, from 1994 to 2018, the proportion of coal consumption in the energy consumption structure of the construction industry decreased by 26.6%, while the proportion of electricity consumption increased by 13.6%. This change is the most remarkable among all types of energy consumption. The transformation and upgrading process of the construction industry provides important reference and inspiration for other industries with high energy consumption. Achieving the green transformation of industries with high energy consumption, which are represented by the construction industry, not only can provide economic benefits to the industry itself but also can offer extensive benefits to consumers and society. Thus, this green transformation contributes to the realization of the dual-carbon goals.

The impact of the proportion of wind power generation on energy competitiveness has been continuously rising. After the proportion reaches 2.66%, the degree of its impact shows a slowly increasing trend (Fig. 8i). This finding indicates that the significance of the effects of wind energy, as an important energy source for energy conservation and environmental protection, still needs to be further enhanced. Wind power is an alternative energy source with unlimited resources and relatively low costs, and its generation holds an important position in the field of renewable energy utilization. Wind power is currently the most technologically mature power-generation method with the best conditions for large-scale development among renewable new energy sources. Promoting energy substitution in an orderly manner and comprehensively constructing non-fossil energy projects, such as wind power, photovoltaic power, hydropower, and nuclear power, are important measures for adjusting the energy structure and achieving sustainable development.

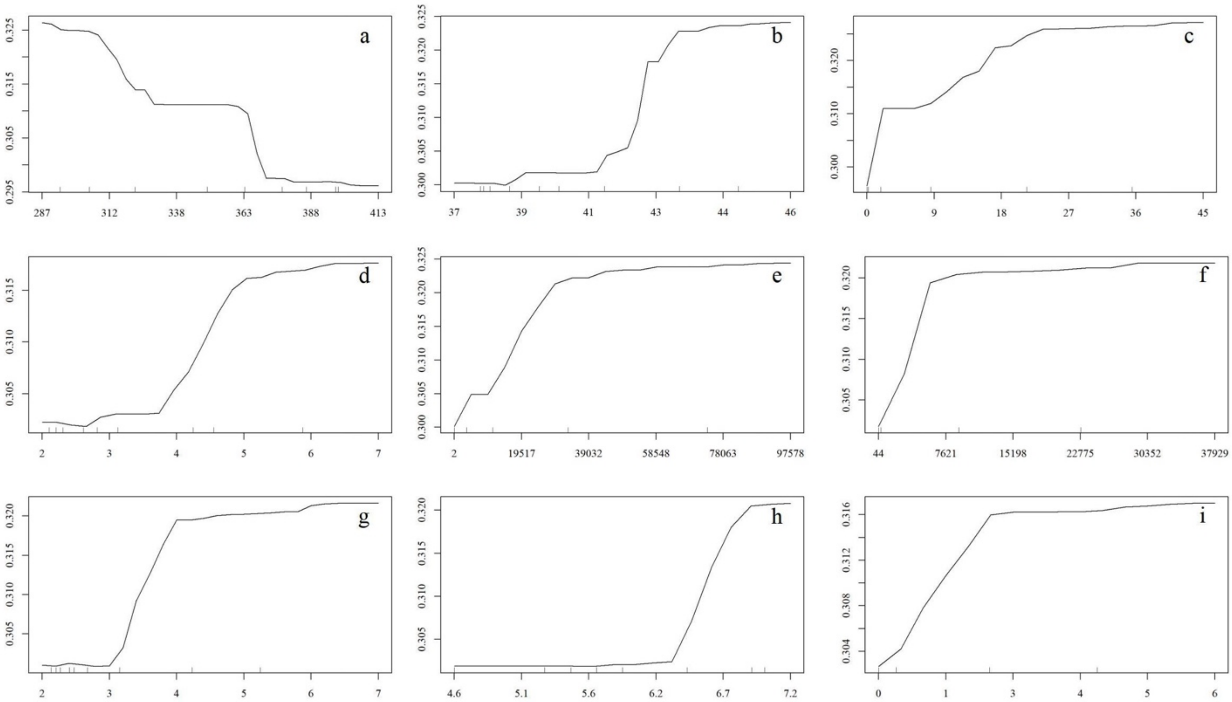

Fig. 8. Partial dependence plots

5.3.2 Analysis of the phased evolution of key factors

According to existing research, the situation of China's energy-related carbon dioxide emissions has undergone three periods. The first is the climbing period from 1980 to 2001, during the early stage of reform and opening-up, when the growth of China's energy consumption was relatively stable. The second is the rapid-rise period from 2002 to 2011, after China's accession to the WTO. During this time, while pursuing rapid economic development, China's energy consumption growth entered a stage of sharp increase. The third is the control period from 2012 to the present. Since entering the new era, the growth rate of China's energy consumption has significantly slowed down because of the active implementation of the energy revolution. Combining the three time periods with significant changes in the data characteristics of energy competitiveness (1980–1999, 2000–2011, and 2012–2020), this study uses the random forest model to analyse sub-samples for identifying the key influencing factors in different periods. The specific method proceeds as follows. Key influencing factors are selected according to a certain proportion. Taking data characteristics and policy changes as the dividing dimensions, the importance of the major categories to which the key influencing factors belong for the energy competitiveness of each year is explored. The evolution law of energy competitiveness is revealed by conducting a horizontal comparison of the importance of each major category and the number of indicators.

Tables 4–6 present the ranking results of the importance of impact factors across three distinct stages based on the IncMSE method. The top five influencing factors in the importance ranking from 1980 to 1999 were the producer price index for petroleum and natural gas industry, the standard coal consumption of power supply, industrial scale of ethylene, industrial scale of caustic soda, and the population using liquefied petroleum gas in urban areas (Table 4). During this period, the categories of fossil energy prices, technological progress, and the scale and proportion of industries with high energy consumption significantly impacted China's energy competitiveness. Specifically, during the energy consumption climb phase, fossil energy prices emerged as a core influencing factor driving the substitution of renewable energy for fossil fuels and enhancing energy competitiveness. The high prices of fossil energy formed a sharp contrast with the relatively low costs of renewable energy, which enhanced the market competitiveness of the latter and played a critical role in optimizing the energy structure. Under the traditional extensive economic growth model, the overcapacity in industries with high energy consumption has led to significant energy consumption and environmental pollution. In this context, the low-carbon transformation of industries with high energy consumption and the improvement in energy utilization efficiency are crucial for energy conservation, emission reduction, and energy competitiveness enhancement.

Table 4. Ranking of impact factors from 1980 to 1999

Influencing factors	1980-1999
Producer price index for petroleum and natural gas industry	1
Standard coal consumption for power supply	2
Ethylene	3
Caustic soda	4
Population using liquefied petroleum gas in urban areas	5
Synthetic ammonia	6
Population using artificial gas in urban areas	7
Processing and conversion efficiency of power generation and station heating	8
Overall labor productivity	9
Total supply of liquefied petroleum gas in urban areas	10
Per capita disposable income of urban residents	11
Crude steel	12
Comprehensive energy consumption per unit in the crude steel industry	13
Number of refrigerators per 100 rural households	14
Proportion of hydropower generation	15
Number of civilian vehicles owned	16
Per capita disposable income of rural residents	17
Line loss rate of power plants	18
Proportion of raw coal consumption	19
Proportion of scientific research, technical services, and geological exploration industry	20
Number of motorcycles per 100 rural households	21
Number of television sets per 100 rural households	22

From 2000 to 2011, the top five influencing factors in importance changed to the industrial scale of soda ash, the number of television sets per 100 rural households, the number of refrigerators per 100 rural households, proportion of construction industry, and the number of motorcycles per 100 rural households (Table 5). During this phase, the accelerated pace of industrialization and urbanization further intensified the impact of industries with high energy consumption on energy competitiveness. Traditional energy consumption by residents also became a significant factor affecting energy competitiveness. The primary contradiction of this historical period is the conflict between the rising living standards driven by rapid economic development and the goals of energy conservation and emission reduction.

Table 5. Ranking of impact factors from 2000 to 2011

Influencing factors	2000-2011	Rank change
Soda ash	1	-
Number of television sets per 100 rural households	2	22→2
Number of refrigerators per 100 rural households	3	14→3
Proportion of construction industry	4	-
Number of motorcycles per 100 rural households	5	21→5
Population using artificial gas in urban areas	6	7→6
Proportion of financial industry	7	-
Population using natural gas in urban areas	8	-
Finished steel	9	-
Mobile phone penetration rate	10	-
Proportion of transport, storage, and postal services	11	-
Proportion of wind power generation	12	-
Standard coal consumption for power supply	13	2→13
Per capita disposable income of rural residents	14	17→14
Proportion of natural gas consumption	15	-
Ethylene	16	3→16
Standard coal consumption for power generation	17	-
Number of private cars per 100 urban households	18	-
Cement	19	-
Flat glass	20	-
Railway operating mileage	21	-
Line loss rate of power plants	22	18→22

From 2012 to 2020, the top five influencing factors in the importance ranking shifted to the population using artificial gas in urban areas, the comprehensive energy consumption per unit in the ethylene industry, the total supply of natural gas in urban areas, the proportion of scientific research, technical services, and geological exploration industries, and the comprehensive energy consumption per unit in the crude steel industry (Table 6). During this period, the role of technological progress in enhancing energy competitiveness became increasingly prominent, while traditional energy consumption by residents continued to exert its influence. Meanwhile, the adjustment of the energy structure significantly progressed. The rapid development of strategic emerging industries with low energy consumption, such as scientific research, technical services, and geological exploration, effectively facilitated energy conservation and consumption reduction. In the process of industrial restructuring, the development of the tertiary sector, including modern services and high-tech industries, emerged as one of the pivotal factors in enhancing energy competitiveness in the new era.

Table 6. Ranking of impact factors from 2012 to 2020

Influencing factors	2012-2020	Rank change
Population using artificial gas in urban areas	1	7→6→1
Comprehensive energy consumption per unit in the ethylene industry	2	-
Total supply of natural gas in urban areas	3	-
Proportion of scientific research, technical services, and geological exploration industry	4	20→-→4
Comprehensive energy consumption per unit in the crude steel industry	5	13→-→5
Population using natural gas	6	-→8→6

in urban areas		
Line loss rate of power plants	7	18→22→7
Internet broadband subscribers	8	-
Proportion of crude oil consumption	9	-
Proportion of wind power generation	10	-→12→10
Per capita disposable income of urban residents	11	11→-→11
Total supply of liquefied petroleum gas in urban areas	12	10→-→12
Number of private cars per 100 urban households	13	-→18→13
Number of refrigerators per 100 rural households	14	14→3→14
Caustic soda	15	4→-→15
Synthetic ammonia	16	6→-→16
Proportion of construction industry	17	-→4→17
Processing and conversion efficiency of power generation and station heating	18	8→-→18
Standard coal consumption for power supply	19	2→13→19
High-speed railway operating mileage	20	-
New energy vehicle sales	21	-
Proportion of thermal power generation	22	-

Overall, between 1980 and 2020, in the context of residents' traditional lifestyles, the influence weight of the population using artificial gas in urban areas rose from the 7th position to the top, while the population using natural gas in urban areas, previously not identified as a key influencing factor, surged to the 6th position. In addition, the total supply of natural gas in urban areas emerged as a newly significant third key influencing factor. Urban gas, as a critical component of the city's energy structure and infrastructure, supplies high-quality gaseous fuel for industrial, commercial, and residential use. Thus, it plays a pivotal role in enhancing the city's energy competitiveness. Improving the level of urban gasification can enhance the quality of life of urban residents, the urban environment, and energy utilization efficiency.

In terms of technological progress, the comprehensive energy consumption per unit in the ethylene industry emerged as the second most critical influencing factor. Meanwhile, the comprehensive energy consumption per unit in the crude steel industry rose from the 13th to the 5th position, and the line loss rate of power plants increased from the 18th to the 7th position. Conversely, the processing and conversion efficiency of power generation and station heating dropped from the 8th to the 18th position, and the standard coal consumption for power supply declined from the 2nd to the 19th position. Therefore, energy efficiency indicators such as unit comprehensive energy consumption in multiple industrial industries occupy a relatively important position in affecting energy competitiveness. With the vigorous development of new technologies and processes in the national power industry, the standard coal consumption for power supply has been decreasing annually, which led to a diminished impact on energy competitiveness. Therefore, accelerating the specialized breakthroughs in energy technology within key sectors, promoting the transformation of industries with high energy consumption from extensive development to high-quality development, and intensifying technological research and development efforts are needed to achieve low-carbon or even decarbonized industrial chains. These efforts will advance the transition of industrial structures with high energy consumption toward low-carbon value chains.

With regard to service industry proportion, the weight of the proportion of scientific research, technical services, and geological exploration industries rose from the 20th position to the 4th, which indicates that the service sector has begun to significantly influence the process of energy competitiveness. On the one hand, comprehensive energy services with energy technology services as one of the contents has become an important development direction of the modern energy industry and plays an important media role in China's energy economy transformation. On the other hand, the service industry, as an important part of the low-carbon economy, has low energy resource consumption and low environmental pollution, which plays an important role in reducing energy intensity.

Regarding residents' new forms of consumption, the number of internet broadband subscribers increased to 8th, the number of high-speed rail business mileage rose to 20th, and the number of new energy vehicle sales improved to 21st. The reason is that the popularization and application of 5G technology have facilitated the rapid development of application scenarios such as the Internet of Things, artificial intelligence, and new-energy vehicles. An increasing number of industries will also enter the electric-energy era. The proportion of electric energy in total energy consumption will continue to grow, and the impact of residents' new forms of consumption will keep rising. This increase highlights the importance of paying attention to the influence of residents' new forms of consumption on energy competitiveness in the new era.

Concerning the energy composition, the consumption of crude oil is the newly added influencing factor and ranked 9th. The proportion of wind power generation fluctuated around the 10th place in the second and third stages. As a newly added influencing factor, the proportion of thermal power generation ranked 22nd. This result indicates that the technological progress in balancing fossil energy and the development of renewable low-carbon energy such as wind power are the key points that need to be focused on in the future. On the one hand, the demand for crude oil and raw coal in China, as the world's largest developing country, will continue to increase quickly with its rapid economic development. However, the pressure on the secure supply of crude oil will increase with the current high-demand energy consumption situation due to the less-favorable resource endowment of petroleum compared with that of natural gas in the country. On the other hand, although China has progressed in terms of renewable energy utilization technologies in recent years, issues such as large-scale construction challenges, unbalanced development, and an irrational energy consumption structure still exist. Nevertheless, these problems insignificantly impact energy competitiveness.

Pertaining to industries with high energy consumption, the ranking of the industrial scale of caustic soda dropped from 4th to 15th, that of the industrial scale of synthetic ammonia decreased from 6th to 16th, and the proportion ranking of the construction industry declined from 4th to 17th. This finding indicates that China has achieved remarkable results in the low-carbon development of industries with high energy consumption in recent years.

Supporting advanced production capacity while phasing out or upgrading outdated capacity is needed to leverage high-quality energy development and facilitate the modernization of China. Other factors, including the per capita disposable income of urban residents, the number of private cars per 100 urban households, the total supply of liquefied petroleum gas in urban areas, and the number of refrigerators per 100 rural households, exhibited fluctuations. However, they experienced minimal changes in their overall importance.

6. Conclusion

6.1 Main findings

The objective entropy weight method is employed to quantitatively assess China's energy competitiveness from 1980 to 2020 based on the conceptual definition of China's energy competitiveness. In addition, the random forest algorithm is utilized to conduct an in-depth analysis of its development process and key influencing factors. The following conclusions are drawn. (1) China's energy competitiveness exhibits an overall upward trend. According to its distribution characteristics, it is categorized into three historical stages: the "slow growth period," the "plateau period," and the "rapid expansion period." (2) In the development of China's energy competitiveness, factors such as technological progress, residents' traditional lifestyles, energy production, and residents' new forms of consumption exert relatively large marginal impacts. (3) The importance of each key influencing factor varies across different stages, which results in distinct temporal variation patterns and nonlinear response relationships.

6.2 Managerial implications

This study offers the following managerial insights for enhancing energy competitiveness:

Fossil energy consumption should be strictly regulated, and the high-quality development of clean energy needs to be promoted. First, we should prioritize the high-quality development of clean energy sources, such as natural gas. We should also actively promote the strategic adjustment and optimization of industrial, energy, and transportation structures to facilitate the clean and low-carbon transformation in industries such as construction, transportation, and others. Second, we should focus on controlling fossil energy consumption and gradually transition to a dual-control system that addresses total carbon emissions and intensity. Third, we should accelerate the research, development, and application of energy-saving and emission-reduction technologies; advocate for green consumption; and promote the adoption of green and low-carbon production practices and lifestyles. These measures are essential for reconciling economic development and carbon reduction goals, systematically advancing efforts to peak carbon emissions, and effectively implementing the carbon neutrality action plan.

Technological progress and green transformation should be promoted while addressing residents' emerging consumption needs. First, we should consider the structural changes in the effect of technological progress on energy competitiveness, as well as its threshold effects. Technological progress and innovation tend to favor clean energy over fossil energy, and the economic and environmental benefits derived from advancements in clean energy technologies are greater. Therefore, the government should actively promote the transition from traditional industries and economic development models to emerging industries and green, low-carbon development models. At the same time, given that China's energy consumption structure remains dominated by fossil fuels and its electricity generation relies primarily on thermal power, policies such as "electricity substitution" and "clean energy substitution" should continue to be implemented in the long term to facilitate the transition of the energy consumption structure. This transition will help achieve a diversified and coordinated transformation of the energy system and establish a supply framework in which multiple energy sources complement each other. Second, the "factorial energy reduction effect" associated with the green transformation of industries with high energy intensity and its implications for energy competitiveness need to be considered. The transformation and upgrading of industries with high energy intensity not only generate economic benefits for the industries themselves but also create broad benefits for consumers and society. Thus, they contribute to the achievement of dual carbon goals. Third, the impact of residents' new forms of consumption on energy competitiveness should not be neglected. The growing demand for emerging consumption serves as an intrinsic driver for regional technological innovation, energy efficiency, and cost reduction. Fourth, the role of non-fossil energy in enhancing future energy competitiveness should be given due consideration. The proportion of non-fossil energy in China's energy consumption structure has remained low in recent years. Efforts should be made to accelerate the optimization of the energy structure, reduce dependence on fossil fuels, and vigorously develop renewable energy sources for advancing the goal of ecological civilization.

6.3 Research limitations and future directions

Although this study considers various factors as thoroughly as possible, certain unavoidable limitations persist due to the lack of research resources and level. First, this study identifies the key factors influencing China's energy competitiveness, but it may fail to fully consider the interactions among these factors. Future research could develop a more dynamic model to better capture these interactions. Second, the entropy weight method used in this study is objective. However, it may not fully capture the complexities and uncertainties involved in measuring energy competitiveness. Subsequent investigations could explore more advanced models and methods, such as machine learning algorithms, to enhance the accuracy and reliability of energy competitiveness assessment.

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