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Research on Green Innovation Efficiency Measurement and Influencing Factors of Listed Power Generation Enterprises in China

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ABSTRACT

Driven by the global transition to low-carbon energy and China's "dual carbon" goals, the power generation industry, as one of the main sources of resource consumption and carbon dioxide emissions, is facing an urgent need for green development. This paper takes A-share listed power generation enterprises from 2014 to 2023 as the research sample, measures green innovation efficiency based on the Data Envelopment Analysis (DEA) model, and identifies key influencing factors by combining a Tobit panel regression model. The study found that: (1) Green innovation efficiency (GIE) is generally low, with significant room for improvement, and shows a "W" pattern of decline followed by increase. Among these, pure technical efficiency (PTE) and scale efficiency (SE) are both at low levels, and there is significant heterogeneity among enterprises. (2) Among external factors, government subsidies have no significant impact, while market attention has a significant positive impact on green innovation efficiency through pure technical efficiency. Among internal factors, innovation level and capital intensity have a significant negative impact, while human resource level and enterprise scale have a significant positive impact, affecting green innovation efficiency through pure technical efficiency and scale efficiency, respectively.

KEYWORDS

Power generation enterprises; Green innovation efficiency; DEA

1. INTRODUCTION

Against the backdrop of global environmental challenges and China's economic development, the green transformation of China's power generation industry is urgent. As one of the main sources of resource consumption and carbon dioxide emissions, the power generation industry faces three major challenges: First, the energy structure is unbalanced. In 2023, thermal power accounted for 66% of the total, while non-fossil energy accounted for only 34% [1], which is significantly below the 39% target for 2025.Second, carbon emissions are a major issue, with the power industry accounting for more than 40% of national carbon emissions. Low-carbon transformation is needed to achieve the goal of reducing coal-fired power carbon emissions by 50% by 2027.Third, energy efficiency needs to be improved. In 2023, the standard coal consumption of coal-fired power generation was 303 grams/kWh, which did not meet the benchmark value, and the utilization hours of wind and solar power were 10-20% lower than the national standard. Technical research and development needs to be strengthened [2, 3]. Listed power generation companies generally face issues such as unclear green innovation paths and a lack of efficiency assessment systems. There is an urgent need to establish scientific measurement methods to identify differences and clarify influencing factors, thereby providing support for government and corporate decision-making.

The concept of green innovation was first proposed by Fussler and James in 1996 and defined as new products and processes that can create value for consumers and businesses while significantly reducing negative environmental impacts [4]. The mainstream method for evaluating green innovation efficiency is data envelopment analysis (DEA) [5] and the model has been innovated and expanded based on different objects and scenarios on the basis of the original model.Examples include the Super-SBM DEA model incorporating undesirable outputs [6], the DEA-Malmquist productivity index model [7], and the SFA-Malmquist productivity index model et al. [8, 9]. Other scholars have used a common frontier-SBM-DEA model that includes non-expected outputs to assess and calculate the green innovation efficiency of Chinese enterprises in two stages [10], and have used a generalized three-stage DEA model to assess the technological innovation efficiency of China's integrated circuit industry [11]. After completing the efficiency measurement, research on influencing factors can be conducted in areas such as policy factors, market mechanisms, and internal corporate factors. For example, using the system GMM estimation method, the impact mechanism of environmental regulations on corporate green technological innovation was explored in depth [12]. Through empirical analysis using a first-order difference generalized moment estimation model, we found that carbon market policies significantly promoted the dynamic adjustment of early investment structures and continuously promoted the green upgrading of production equipment and green innovation in production processes [13]. Some scholars have also used the Tobit model to further explore the factors affecting innovation efficiency from the perspective of corporate characteristics [14]. Currently, efficiency measurement research is divided into different levels. There are abundant results at the macro level, but relatively few studies at the micro level of enterprises. Existing research methods and model innovations can provide a research basis for this study, but there is relatively little research related to the power industry, which needs to be further supplemented and studied in depth.

2. MODEL CONSTRUCTION

2.1. SBM Model Containing Unexpected Outputs

This paper selects the SBM model based on non-expected output as the model for evaluating the green innovation efficiency of power generation enterprises. On the one hand, traditional DEA models are based solely on expected output. However, numerous studies have shown that unexpected output should also be taken into account. Focusing solely on expected output and ignoring the slack in inputs and outputs will result in an overestimation of efficiency. On the other hand, traditional DEA models are radial and angular, which can cause certain deviations in measurement results. On the other hand, traditional DEA models are radial and angular, which can cause certain deviations in measurement results. Considering non-radial and non-angular SBM models can effectively avoid this problem and is more conducive to improving the accuracy of measurement result analysis. Based on this, the green innovation efficiency evaluation model constructed is as follows:

$$\rho^* = \min \frac{1 - \frac{1}{m}\sum_{i=1}^{m} s_i^- / x_{i0}}{1 + \frac{1}{q_1 + q_2}\left(\sum_{r=1}^{q_1} s_r^+ / y_{r0} + \sum_{r=1}^{q_2} s_r^{b-} / b_{r0}\right)}$$

$$s.t\begin{cases} \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = x_{i0},\ i = 1,\ 2,\ ...,\ m \\ \sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{r0},\ \ r = 1,\ 2,\ ...,\ q_1 \\ \sum_{j=1}^{n} \lambda_j b_{rj} + s_r^{b-} = b_{r0},\ \ r = 1,\ 2,\ ...,\ q_2 \\ \sum_{j}^{n} \lambda_j = 1 \\ \lambda_j \geq 0,\ s_i^- \geq 0,\ \ s_r^+ \geq 0 \\ i = 1, 2, ..., m; r = 1, 2, ..., q, j = 1, 2, ..., n(j \neq k) \end{cases} \tag{1}$$

In the formula, ρ is the target efficiency value. For DMU_j (j = 1, 2, ..., n), each DMU has m types of inputs, denoted as x_i (i = 1, 2, ..., m), and can simultaneously produce q_1 types of good outputs, denoted as y_r (r = 1, 2, ..., q_1) and q_2 types of defective outputs, denoted as b_r(r=1, 2, ..., q_2); x_{ij} is the i-th input factor of the j-th listed power generation enterprise. b_{rj} is the rth non-expected output of the jth listed power generation enterprise. The more expected output, the better, while the opposite is true for non-expected output. λ_j is the weight of the cross-sectional observation values of each DMU. The subscript k refers to the DMU being measured. s_i^-, s_r^+, and s_r^{b-} refer to input redundancy, insufficient expected output, and non-expected output redundancy, respectively.

2.2. Tobit Model

The Tobit model is one of the classic methods used to conduct factor analysis. Assuming that the actual observed value is the independent variable, denoted by xi; the green innovation efficiency of power companies is the dependent variable, denoted by yi, and the value range of yi is between 0 and 1. The relationship between yi and xi is shown in the following formula:

$$y_i^* = \beta^T x_i + e_{i,} e \sim N\ (0,\ \ \delta^2) \tag{2}$$

Among them,

$$y_i = \begin{cases} c_t^-, y_i^* \leq c_t^- \\ y_i^*, c_t^- < y_i^* \leq c_t^+ \\ c_t^+, y_i^* > c_t^+ \end{cases} \tag{3}$$

3. VARIABLE SELECTION AND DATA SOURCES

3.1. Selection of Input-Output Indicators

Referring to the research of MA Wen-bin and ZHu Huan [14] (2024), Cao Z X et al. [15] (2023), and Qian Li et al. [10] (2021), an evaluation index system is constructed as shown in Table 1.

Table 1. Green Innovation Efficiency Evaluation Index System

Indicator type	Name	Measurement	Source
R&D Input	R&D expenditure Input	R&D Expenditure	MA Wen-bin and ZHu Huan [14] (2024)
	R&D Labor Input	Number of R&D Personnel	MA Wen-bin and ZHu Huan [14] (2024)
Labor Input	Human Resource Input	Total Employees	MA Wen-bin and ZHu Huan [14] (2024)
Resource Input	Energy Input	Total Energy Consumption	Cao Z X et al. [15] (2023)
Expected Output	Innovation Output	Annual Green Patent Applications	Qian Li et al. [10] (2021)
	Economic Output	Electricity Sales Revenue	Qian Li et al. [10] (2021)
	Industrial Upgrading	Green Electricity Sales Revenue	PAN Jianjun et al. [16] (2023)
Unexpected Output	Pollutant Output	Comprehensive Environmental Pollution Index	Cao Z X et al. [15] (2023)
	Carbon Emissions	CO_2 Emissions	

3.2. Setting of Influencing Factor Variables

The level of green innovation efficiency in an enterprise is the result of the combined effects of numerous external and internal factors. This paper draws on the methods used by Qian Li et al. [10] (2021) and You Da-ming et al. [17] (2022) to select influencing factors, and combines the characteristics of green innovation in listed power generation companies to select the influencing factor indicator system shown in Table 2.

Table 2. Indicators of Determinants for Green Innovation Efficiency

Variable Type		Variable Name	Variable Description	variable symbol
Explained Variables		Green Innovation Level	Green innovation efficiency	GIE_{it}
		Technological Innovation Level	Pure technical efficiency	PTE_{it}
		Scale Level	Scale efficiency	SE_{it}
Explanatory Variables	External Factors	Government support	Government subsidy amount	Gs_{it}
		Market Attention	Annual turnover rate of stocks	MA_{it}
	Internal Factors	Level of Innovation	R&D expenditure / Operating revenue	EI_{it}
		Human Resource Level	Proportion of employees with bachelor's degrees	$Labor_{it}$
		Environmental Awareness	ESG rating score	ESG_{it}
		Firm Size	Natural logarithm of total assets	$Size_{it}$
		Profitability	Return on assets (ROA)	ROA_{it}
		Capital Intensity	Operating revenue / Total assets	$Capi_{it}$

Coelli (1998) first proposed the Tobit regression method, which subsequently gave rise to the DEA-Tobit two-stage method. This paper draws on his research and adopts the two-stage SBM-Tobit analysis method, namely, in the first stage, input-output indicators are used to measure the efficiency values of different units, and in the second stage, the efficiency values from the first stage are used as the explained variable in the regression analysis of the second stage to determine the main factors affecting unit efficiency. The regression model is shown in Table 4-6:

$$GIE_{it} = \alpha_0 + \alpha_1 ER_{it} + \alpha_2 GS_{it} + \alpha_3 MA_{it} + \alpha_4 EI_{it} + \alpha_5 Labor_{it} + \alpha_6 ESG_{it} + \alpha_7 Size_{it} + \alpha_8 ROA_{it} + \alpha_9 Capi_{it} + \varepsilon_{it} \tag{4}$$

$$PTE_{it} = \alpha_0 + \alpha_1 ER_{it} + \alpha_2 GS_{it} + \alpha_3 MA_{it} + \alpha_4 EI_{it} + \alpha_5 Labor_{it} + \alpha_6 ESG_{it} + \alpha_7 Size_{it} + \alpha_8 ROA_{it} + \alpha_9 Capi_{it} + \varepsilon_{it} \tag{5}$$

$$SE_{it} = \alpha_0 + \alpha_1 ER_{it} + \alpha_2 GS_{it} + \alpha_3 MA_{it} + \alpha_4 EI_{it} + \alpha_5 Labor_{it} + \alpha_6 ESG_{it} + \alpha_7 Size_{it} + \alpha_8 ROA_{it} + \alpha_9 Capi_{it} + \varepsilon_{it} \tag{6}$$

3.3. Data Sources and Processing

3.3.1. Data Sources

This study focuses on listed power generation companies in China. Based on the "Guidelines for the Classification of Listed Companies by Industry," data from 2014 to 2023 was selected. Companies that were marked as 'ST' or "*ST" during the reporting period, companies with insufficient data, and companies with abnormal data were excluded. Finally, 42 listed power generation companies were selected. The original data sources for the input indicators and expected output indicators are the CSMAR database, annual reports of listed companies, and the National Intellectual Property Administration. In selecting output indicator data, we followed the approach of Li Hongkuan et al. [11] (2020), taking into account the time lag in output and selecting data from the following year.

3.3.2. Descriptive Analysis

Table 3. Descriptive Analysis of Variables

Variable	Obs	Mean	Std. dev.	Min	Max
GIE_{it}	378	0.659	0.256	0.123	1.000
PTE_{it}	378	0.753	0.253	0.220	1.000
SE_{it}	378	0.865	0.129	0.273	1.000
Gs_{it}	378	0.862	2.760	0.000	28.730
MA_{it}	378	3.060	3.385	0.163	27.037
EI_{it}	378	0.013	0.020	0.000	0.145
$Labor_{it}$	378	0.374	0.165	0.012	0.833
ESG_{it}	378	4.312	0.069	3.910	4.485
$Size_{it}$	378	24.145	1.422	21.345	27.072
ROA_{it}	378	0.021	0.040	-0.290	0.162
$Capi_{it}$	378	0.310	0.174	0.022	1.108

3.3.3. Multicollinearity Test

To avoid multicollinearity issues, the correlation coefficients between explanatory variables in the model are tested.

Table 4. VIF Test for Independent Variables

Variable	VIF	1/VIF
Gs_{it}	2.02	0.494773
MA_{it}	1.52	0.655773
EI_{it}	1.32	0.755117
$Labor_{it}$	1.31	0.764961
ESG_{it}	1.23	0.811114
$Size_{it}$	1.12	0.893891
ROA_{it}	1.07	0.932032
$Capi_{it}$	1.02	0.98308
Mean VIF	1.33	

Generally speaking, if both the maximum VIF is greater than 10 and the average VIF is greater than 1, it can be determined that there is multicollinearity. According to the results in Table 4, the VIF values of the variables are all below 10, indicating that the variables selected in this paper do not exhibit multicollinearity.

4. ANALYSIS OF RESULTS

4.1. Analysis of Green Innovation Efficiency Measurement Results

Using Dearun software, input-output indicators of each enterprise were incorporated into the SBM model to compute green innovation efficiency (GIE) for 42 listed power generation firms during 2014-2023.The efficiency was further decomposed into pure technical efficiency (PTE) and scale efficiency (SE). Due to space constraints, only aggregated green innovation efficiency results are presented. As shown in Table 5, among 420 decision-making units (DMUs):

82 DMUs achieved optimal efficiency (efficiency value = 1)

59 DMUs demonstrated high efficiency ($0.8 \leq$ efficiency < 1)

156 DMUs registered medium efficiency ($0.6 \leq$ efficiency < 0.8)

124 DMUs exhibited low efficiency (efficiency < 0.6)

Notably, 66.67% of DMUs showed suboptimal efficiency (≤ 0.8), The proportion of DMUs that have not achieved optimal efficiency reaches 80.48%, indicating significant room for improvement in the green innovation efficiency of listed power generation enterprises. Meanwhile, 72.62% of DMUs failed to achieve optimal pure technical efficiency (PTE), and 72.14% fell short of optimal scale efficiency (SE), both indicating substantial potential for improvement.

Table 5. Green Innovation Efficiency Measurement Results

DMU	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	Mean
1	0.792	0.738	0.715	0.688	0.675	0.667	0.628	0.605	0.610	0.773	0.689
2	0.268	0.238	0.221	0.208	0.280	0.278	0.284	0.551	0.648	0.769	0.374
3	0.234	0.252	0.177	0.133	0.223	0.622	0.610	0.595	0.585	0.845	0.428
4	0.484	0.425	0.425	0.397	0.373	0.397	0.218	0.212	0.217	0.291	0.344
5	1.000	0.735	0.738	0.720	0.688	0.714	0.693	0.670	0.643	0.853	0.745
6	0.273	0.259	0.252	0.171	0.154	0.148	0.146	0.126	0.149	0.724	0.240
7	0.808	0.756	0.661	0.650	0.632	0.605	0.626	0.623	0.592	0.399	0.635
8	1.000	0.481	0.777	0.410	1.000	0.536	0.545	0.749	0.855	1.000	0.735
9	1.000	0.539	0.462	0.446	0.428	0.483	1.000	1.000	1.000	1.000	0.736
10	0.907	0.806	0.745	0.733	0.706	0.710	0.684	0.580	0.570	0.728	0.717
11	1.000	0.926	0.879	0.812	0.692	0.773	0.813	1.000	1.000	1.000	0.890
12	1.000	1.000	1.000	1.000	1.000	1.000	0.602	0.681	0.665	1.000	0.895
13	0.297	0.417	0.397	0.311	0.382	0.690	0.650	0.641	0.287	0.775	0.485
14	1.000	1.000	1.000	0.854	0.951	0.983	1.000	1.000	1.000	1.000	0.979
15	0.393	1.000	0.262	0.281	0.270	0.264	0.267	0.662	0.652	0.925	0.498
16	1.000	1.000	1.000	0.881	1.000	1.000	0.848	0.829	0.837	1.000	0.940
17	1.000	0.256	0.236	0.219	0.199	0.193	0.185	0.214	0.758	1.000	0.426
18	1.000	1.000	0.847	0.840	0.821	0.820	0.796	0.304	0.516	1.000	0.794
19	0.299	0.277	0.288	0.696	0.749	0.790	0.769	0.768	0.733	0.904	0.627
20	0.367	0.828	0.834	0.802	0.852	1.000	1.000	1.000	0.860	0.936	0.848
21	0.146	0.172	0.123	0.157	0.578	0.599	0.586	0.588	0.579	0.720	0.425
22	0.755	0.847	0.698	0.692	0.678	0.642	0.642	0.638	0.650	0.833	0.708
23	1.000	0.404	0.436	1.000	0.898	1.000	1.000	1.000	1.000	1.000	0.874
24	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
25	0.741	0.612	0.600	0.630	0.577	0.595	0.597	0.598	0.597	0.799	0.635
26	0.820	0.837	0.752	0.771	0.658	1.000	0.938	1.000	1.000	1.000	0.878
27	0.288	1.000	0.526	0.822	0.476	0.644	0.775	0.710	0.662	0.881	0.678
28	1.000	1.000	1.000	0.513	0.255	0.223	0.219	0.223	0.221	1.000	0.565
29	1.000	1.000	0.810	0.717	0.668	0.673	0.696	0.671	0.684	0.827	0.775
30	0.849	0.785	0.829	0.775	0.769	0.773	0.712	0.714	0.693	0.797	0.770
31	0.235	0.156	0.682	0.653	0.625	0.620	0.635	0.594	0.611	0.766	0.558
32	0.247	0.223	0.232	0.201	0.194	0.192	0.186	0.239	0.227	0.222	0.216
33	0.231	0.142	0.714	0.694	0.650	0.621	0.645	0.612	0.613	0.847	0.577
34	0.789	0.511	0.480	0.874	0.871	0.598	0.636	0.660	0.663	0.736	0.682
35	1.000	1.000	1.000	0.423	0.747	0.759	0.783	0.716	0.762	0.769	0.796
36	1.000	1.000	0.932	1.000	0.716	0.653	0.653	0.664	0.636	0.817	0.807
37	0.850	0.814	0.838	0.750	0.726	0.703	0.714	0.690	0.644	0.761	0.749
38	1.000	1.000	0.874	0.830	0.783	0.744	0.745	0.738	0.685	0.880	0.828
39	0.263	0.810	0.807	0.792	0.788	0.786	0.729	0.749	0.759	0.858	0.734
40	1.000	0.875	0.800	0.834	0.705	0.804	0.711	0.698	0.633	1.000	0.806
41	0.497	0.625	0.657	0.584	0.574	0.625	0.632	0.607	0.584	1.000	0.638
42	1.000	0.796	0.697	0.667	0.653	0.630	0.630	0.588	0.594	0.790	0.704
Mean	0.710	0.680	0.652	0.634	0.635	0.656	0.648	0.655	0.659	0.839	

Overall, the green innovation efficiency (GIE) of power generation enterprises exhibits an observable "W-shaped" trajectory, characterized by an initial decline followed by a rebound, while maintaining a relatively low aggregate level. Throughout the study period, both pure technical efficiency (PTE) and scale efficiency (SE) demonstrate minor fluctuations with marginal differences between them, contributing comparably to environmental efficiency as illustrated in Figure 1.

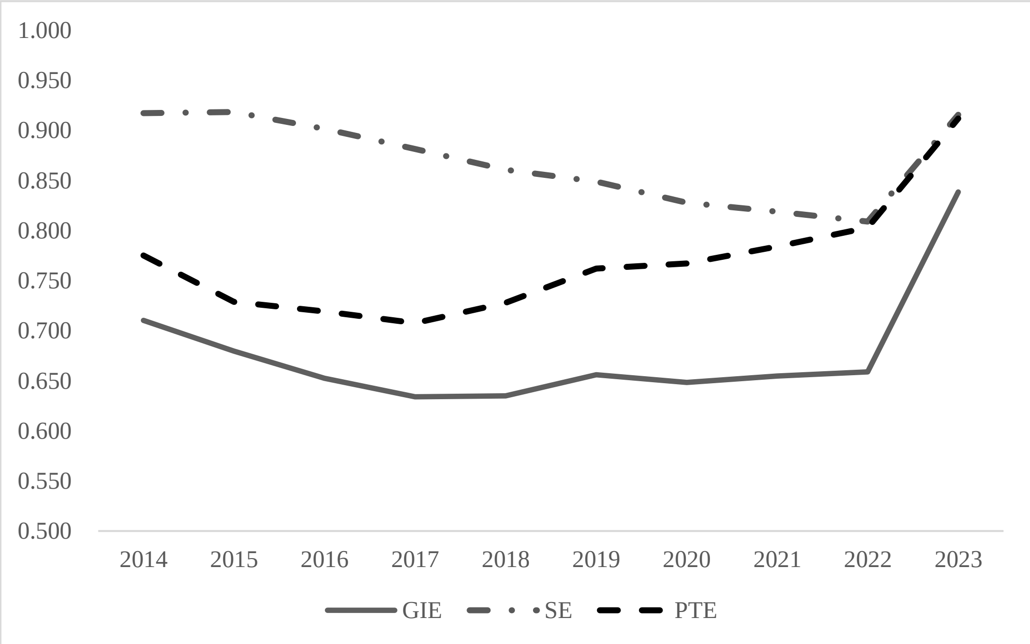

Figure 1. Green innovation efficiency and its decomposition of listed power generation companies in China from 2014 to 2023

Based on the input-output indicator data of 42 listed power generation enterprises, the annual average values of green innovation efficiency (GIE), pure technical efficiency (PTE), and scale efficiency (SE) for China's listed power generation companies from 2014 to 2023 were calculated, as shown in Table 6.The average green innovation efficiency (GIE), of listed power generation companies in China is 0.487, indicating that there is considerable room for improvement in the green innovation efficiency of Chinese power generation companies.The average scale efficiency (SE) and average pure technical efficiency (PTE) were 0.797 and 0.617, respectively, indicating relatively low efficiency levels, which can be increased by expanding company size and advancing technological progress.

Table 6. Efficiency Evaluation: Green Innovation/Scale/Pure Technical Efficiencies of China's Listed Power Companies (2014-2023)

Efficiency	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	Mean
GIE	0.686	0.583	0.472	0.473	0.434	0.422	0.411	0.391	0.404	0.597	0.487
PTE	0.734	0.660	0.572	0.586	0.577	0.574	0.591	0.556	0.563	0.751	0.617
SE	0.925	0.879	0.843	0.820	0.777	0.753	0.724	0.721	0.725	0.802	0.797

4.2. Empirical Analysis of Influencing Factors

Using Stata software, the Tobit model was applied to examine the factors influencing the green innovation efficiency of listed power generation companies in China. First, descriptive analysis and collinearity tests were conducted, with detailed results presented in Table 3 and Table 4. Then, regression analysis was performed, and the regression results are shown in Table 7.

Table 7. Regression Results Analysis

Variable	GIE_{it}	PTE_{it}	SE_{it}
Gs_{it}	-0.006	-0.007	-0.003
MA_{it}	0.014^{***}	0.014^{**}	0.005
EI_{it}	-1.876^{**}	-1.392	-1.344^{***}
$Labor_{it}$	0.081^{**}	0.104^{***}	0.004^{*}
ESG_{it}	-0.035	-0.169	0.053
$Size_{it}$	0.021^{*}	0.027^{*}	0.049^{***}
ROA_{it}	0.469	0.572	0.316
$Capi_{it}$	-0.541_{it}	-0.516^{***}	-0.177^{***}

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Analyzing the impact of external factors, government support intensity (Gs_{it}) showed no significant effect on green innovation efficiency. However, market attention intensity (MA_{it}) exhibited a significantly positive correlation with both green innovation efficiency and pure technical efficiency. This suggests that market attention primarily enhances green innovation efficiency by improving pure technical efficiency."

In terms of the impact of internal corporate factors, innovation level (EI_{it}) significantly negatively affects green innovation efficiency and scale efficiency. Technological innovation primarily manifests through research and development intensity, where its corresponding economic and innovation outputs exhibit temporal lag. While serving as an economic investment, it increases corporate costs, leading to a negative correlation between technological innovation intensity and green innovation levels during the study period. Human resources level ($Labor_{it}$) and company size ($Size_{it}$) are significantly positively correlated with green innovation efficiency, pure technical efficiency, and scale efficiency. Notably, human resources level has a more pronounced effect on pure technical efficiency, while company size has a stronger influence on scale efficiency. Conversely, capital intensity ($Capi_{it}$) is significantly negatively correlated with these efficiencies, likely because the sunk costs in the power sector constrain efficiency and result in a negative impact.

5. CONCLUSION AND RECOMMENDATIONS

5.1. Conclusion

This paper selects 42 listed power generation companies as research objects, selects input-output indicators based on the connotation of green innovation efficiency and the characteristics of the power industry, measures their green innovation efficiency, and selects the Tobit model for factor analysis based on the characteristics of the measurement results. The main conclusions are as follows:

(1) Empirical research indicates that the green innovation efficiency of China's listed power generation companies is generally suboptimal, with over 80% of the sampled firms exhibiting a comprehensive efficiency score below 1, suggesting substantial room for improvement in the industry. Further decomposition of efficiency metrics reveals that these companies not only suffer from low pure technical efficiency but also generally fail to achieve optimal scale efficiency. Notably, there are significant disparities in efficiency levels across different enterprises.

(2) Green innovation efficiency and pure technical efficiency exhibit a "W"-shaped fluctuation pattern, first decreasing and then increasing, with a relatively consistent trend. Scale efficiency also shows a similar fluctuation pattern, first decreasing and then increasing, but with greater volatility. The gap between scale efficiency and pure technical efficiency indicates that a company's scale

efficiency is mismatched during its development process, and that technical efficiency has a significant impact on green innovation efficiency.

(3) Among external factors, government support has no significant impact, while market attention has a significant positive correlation. Among internal factors, innovation level and capital intensity have a significant negative impact, while human resource level and enterprise scale have a significant positive impact. Other factors have no significant impact.

5.2. Countermeasures and Suggestions

As for the government, it should adjust the direction and intensity of subsidies in a timely manner, strengthen investment in new energy, improve the accuracy of subsidy allocation, and improve evaluation and supervision mechanisms.

For enterprises: First, adjust the capital investment structure, shift from extensive investment to technology-intensive investment, focus on digital upgrading and green technology, and increase investment and research and development in energy-saving and carbon-reduction technologies. Second, enhance technological innovation capabilities, strengthen talent cultivation, align human resource development with the company's technological capabilities, and expand the company's scale at the appropriate time to increase market share, thereby enhancing the company's green innovation capabilities.

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