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Analyzing Enterprises' Environmental Performance Factors Using the Three-stage DEA Model under the Green Economic Development

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Abstract: To address the growing concerns of energy conservation and emission reduction (ECER), the pharmaceutical industry has been the target of government policies designed to foster innovation and promote sustainable growth. These policies emphasize the creation of a market-driven framework for green technology innovation, where environmental performance evaluation plays a pivotal role for pharmaceutical enterprises. This study investigates the environmental performance of 100 pharmaceutical companies in China using a three-stage Data Envelope Analysis (DEA) framework enhanced by the Bootstrap Malmquist DEA (BMDEA) model. The DEA-Malmquist index measures dynamic changes in environmental performance, while the Bootstrap-DEA approach corrects potential biases and enhances the evaluation's robustness. Additionally, panel Quantile Regression and review Quantile Regression methods are utilized to examine environmental performance factors. The analysis reveals that the average technical efficiency index of pharmaceutical enterprises is 1.224, indicating an annual growth rate of 2.6%, which reflects the effectiveness of management practices. Over five years, pure technical efficiency improved by 4.9%, signaling better resource utilization. However, scale efficiency declined by 2.5% on average, suggesting that enterprise size may limit improvements in environmental performance. Despite these challenges, the overall trend in environmental performance shows improvement, driven by factors such as economies of scale, technological maturity, environmental awareness, public pressure, and corporate innovation. Notably, the impact of these factors varies across different quantiles. Pharmaceutical companies should focus on optimizing their scale and intensifying innovation efforts to further enhance environmental performance. This study's findings provide valuable insights for policymakers and industry leaders seeking to improve environmental efficiency and promote sustainable development within the pharmaceutical sector.

Keywords: BMDEA model; Three-stage DEA; Pharmaceutical Industry; Environmental Efficiency; Panel Quantile Regression; Review Quantile Regression.

1. Introduction

The pharmaceutical industry is an integral part of China's national economy and has made outstanding contributions to the growth of China's economy. Environmental issues have become increasingly prominent with the continuous development of the green economy. Relevant government departments have formulated a series of environmental policies. The government promotes green development and builds a market-oriented green technology innovation system. Environmental performance evaluation is crucial for enterprises in the pharmaceutical sector [1].

The environmental problems of pharmaceutical enterprises are getting more and more attention from the government. The government has also strongly supported enterprises' Research and Development (R&D) investment. Society also pays great attention to enterprise environmental issues. Green innovation and pollutant emissions are currently among the hottest topics in enterprise environmental behavior research. Asif (2022) used quantitative research methods and sampling to study the sustainability impact of government procurement strategies on the supply chain of pharmaceutical enterprises [2]. Xu et al. (2021) explored the relationship among government subsidies (including government R&D and non-R&D subsidies), R&D investment, and innovation performance of Chinese pharmaceutical-listed enterprises from 2009 to 2015 [3]. Peng et al. (2021) studied heavily polluting enterprises' dual goals and environmental behavior choices. They also discussed the internal selection logic of enterprise environmental behavior using a multinomial logic model [4]. Yang et al. (2019) took the data from 125 Chinese pharmaceutical enterprises from 2010 to 2016 as the research object to analyze the influencing factors of pharmaceutical enterprise social responsibility [5]. López-Toro et al. (2021) implemented structural equation modeling using partial least squares and analyzed the relationship between environment, society, governance, dispute indexes, and financial performance [6]. Qomariah and Nursaid (2021) examined the role and impact of environmental performance, intellectual capital, and enterprise social responsibility on improving pharmaceutical enterprises' profitability and financial performance on the Indonesia Stock Exchange [7]. Nguyen (2021) evaluated and analyzed the impact of Vietnamese pharmaceutical enterprises' internal control elements on environmental performance through the questionnaire method [8]. Most research focuses on environmental issues regarding resource consumption, pollutant emissions, and human resource management. Besides, some scholars study the relationship among pharmaceutical enterprises' social responsibility, financial performance, and environmental performance. There are relatively few studies on the factors influencing the environmental performance of pharmaceutical enterprises. This work studies the environmental performance of pharmaceutical enterprises from the perspective of input and output. It also analyzes the influencing factors of the environmental performance of pharmaceutical enterprises from the perspectives of internal and external factors.

In the environment of green economic development, the Bootstrap Malmquist Data Envelopment Analysis (BMDEA) model is constructed based on the three-stage Data Envelopment Analysis (DEA) model taking the data of 100 pharmaceutical enterprises in China as the research object. The DEA-Malmquist index method is used to measure the environmental performance value of pharmaceutical enterprises. The Bootstrap-DEA method is introduced to correct the environmental performance value, and an index evaluation system is built. In addition, the influencing factors of the environmental performance of pharmaceutical enterprises are analyzed. This work aims to improve the environmental performance level of pharmaceutical enterprises, enhance their innovation capabilities, and provide a basis for enterprise decision-making optimization.

2. The Model and Method of Environmental Performance Evaluation for Pharmaceutical Enterprises

2.1. The Connotation of Enterprise Environmental Performance

Currently, there is no uniform standard for defining environmental performance. ISO14001 environmental management system defines environmental performance as an environmental management system effectiveness obtained by an organization based on environmental objectives and policies through the establishment, implementation, maintenance, and continuous improvement of various environmental factors [9]. From the perspective of the relationship between enterprise behavior and the environment, enterprise environmental performance results from an enterprise's efforts to reduce the external environment. It includes the direct impact of the enterprise on the environment in the process of production and operation and the degree of awareness of environmental protection in the project's development [10]. From the perspective of performance and management, the relationship between enterprise environmental management and enterprise environmental performance is a mutual influence. From the standpoint of the relationship between environmental performance and economic performance, the conclusions put forward by foreign scholars include three points. Enterprise environmental performance is positively correlated, negatively correlated, and uncorrelated with economic performance. Enterprise environmental performance is understood from both narrow and broad perspectives. In a narrow sense, enterprise environmental performance refers to an index system that can be determined and measured by quantitative criteria [11]. In a broad sense, enterprise environmental performance refers to the continuous improvement of comprehensive non-quantitative efficiencies such as pollution prevention, resource utilization, and ecological impact through a non-monetized and non-quantitative index system [12].

2.2. Research on Common Methods of Enterprise Environmental Performance Evaluation

For enterprise environmental performance, common research methods include Fuzzy Comprehension Evaluation, Analytic Hierarchy Process, Back Propagation, and DEA [13]. The advantages and disadvantages of the different methods are compared, as shown in Fig. 1.

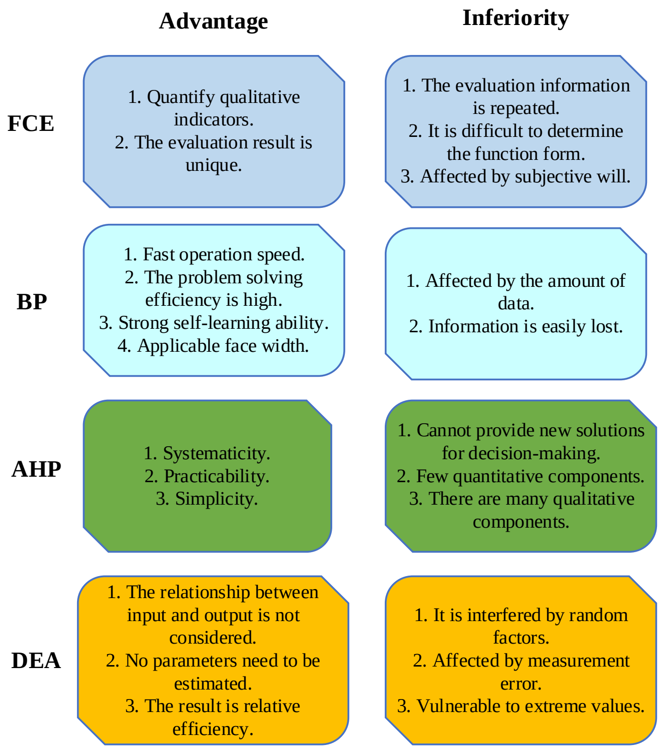

Figure 1. Analysis of the advantages and disadvantages of common methods

From Fig. 1, each method has its advantages and disadvantages. However, DEA has the most obvious advantages and does not need to consider the production function relationship between input and output. It also does not require any parameters or weights to be estimated in advance, avoiding subjective factors. Decision Marking Units (DMU) result in relative efficiency, independent of dimensions.

There is a specific relationship between environmental performance evaluation and environmental responsibility fulfilment, as shown in Fig. 2.

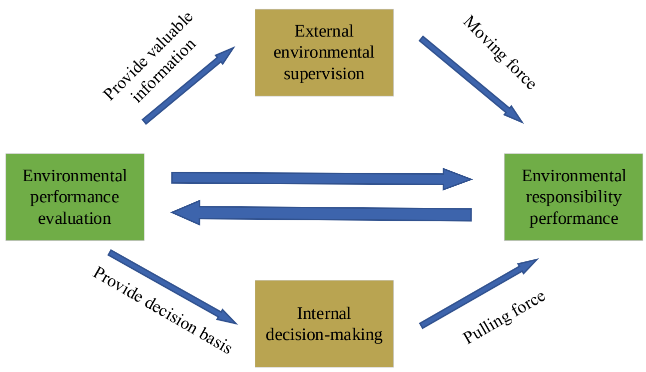

Figure 2. The relationship between environmental performance evaluation and environmental responsibility fulfilment

Environmental performance evaluation can provide valuable information for environmental supervision, supervise the performance of microeconomic entities' environmental responsibilities, and offer a basis for internal decision-making optimization [14]. Then, enterprises are encouraged to actively implement environmental protection behaviors. Therefore, external regulatory authorities and internal management of enterprises jointly promote the implementation of enterprise environmental responsibilities [15].

2.3. Construction of Environmental Performance Evaluation Index System for Pharmaceutical Enterprises

Enterprise environmental performance involves a wide range of content. It should reflect not only the utilization of enterprise resources and energy but also the discharge and utilization of waste. It should also reflect the enterprise's environmental management capabilities [16]. Here, the environmental and financial performance is included in the environmental performance evaluation index. The resource consumption and environmental protection input indexes are selected as the input indexes according to the principles of combining scientific and comprehensive, feasibility and reliability, and qualitative and quantitative [17]. Economic development indexes are used to express expected output indexes. Environmental pollution emissions are non-expected outputs. A system of environmental performance evaluation indexes for pharmaceutical enterprises is constructed, as displayed in Fig. 3.

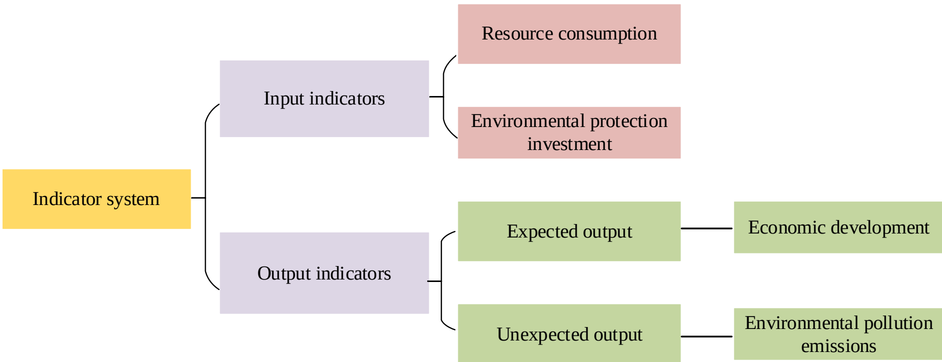

Figure 3. Environmental performance evaluation index system of pharmaceutical enterprises

2.4. BMDEA Model Construction

The BMDEA model combines the DEA method, the Bootstrap method, and the Malmquist exponential analysis method. The Malmquist index is used to analyze the dynamic change rate of environmental performance. The Bootstrap-DEA method is used to correct the environmental performance value to avoid the interference of random factors and small samples.

2.4.1. Three-stage DEA model theory

American operations researcher Charles and others first proposed the DEA model in 1978. It is a commonly used method to examine the relative effectiveness of multi-input and multi-output decision units through computational efficiency [18]. Fried et al. explored how to introduce environmental factors and random perturbations into the DEA model and proposed a three-stage DEA model [19].

In the first stage, the DEA is divided into two models: Charnes Cooper Rhodes (CCR) and Banker Charnes Cooper (BCC) [20]. The output orientation of minimizing input is realized under the determined output, and the input orientation of maximizing output is realized under the determined input. Suppose there are n decision units. It is assumed that the input vector of a decision unit DMU in activity is $X = (x_1, x_2, \cdots, x_m)^T$, and the output vector is $Y = (y_1, y_2, \cdots, y_s)^T$. (X, Y) indicates the entire activity of DMU. The input vector of the $j(j = 1,2,\cdots,n)$ decision unit DMU_j in n DMUs is $X_i = \left(x_{1i}, x_{2j}, \cdots, x_{mj}\right)^T > 0$, and the output vector is $Y_i = \left(y_{1i}, y_{2j}, \cdots, y_{sj}\right)^T > 0$. For $j_0(1 \leq j_0 \leq n)$, the model is constructed from both output and input perspectives [21]. The input-based output is constant, and the CCR model expression for the minimum input is shown in Eq. (1).

$$\begin{cases} min & [\varphi - \varepsilon([e^-]^T S^- + [e^+]^T S^+)] = V_D \\ \text{s.t.} & \sum_{j=1}^{n} X_j\lambda_j + S^- = \varphi X_0 \\ & \sum_{j=1}^{n} Y_j\lambda_j - S^+ = Y_0 \\ & \lambda_j \geq 0 (j = 1,2,\cdots,n); S^+ \geq 0; S^- \geq 0 \end{cases} \quad (1)$$

The output-based input is unchanged, and the output reaches the largest CCR model [22], as expressed in Eq. (2).

$$\begin{cases} max & [\alpha + \varepsilon[([e^-]^T S^- + [e^+]^T S^+)]] = V_D \\ \text{s.t.} & \sum_{j=1}^{n} X_j\lambda_j + S^- = X_0 \\ & \sum_{j=1}^{n} Y_j\lambda_j - S^+ = \alpha Y_0 \\ & \lambda_j \geq 0 (j = 1,2,\cdots,n); S^+ \geq 0; S^- \geq 0 \end{cases} \quad (2)$$

In Eq. (2), λ_j represents the combined weights of the decision unit DMU_j. S^+ and S^- represent relaxation vectors. φ and α represent the relative efficiency of evaluation.

Besides, the relative technical effectiveness between sectors is evaluated. BCC model can be expressed as:

$$\begin{cases} min & \varphi = V_D \\ \text{s.t.} & \sum_{j=1}^{n} X_j\lambda_j + S^- = \varphi X_0 \\ & \sum_{j=1}^{n} Y_j\lambda_j - S^+ = Y_0 \\ & \sum_{j=1}^{n} \lambda_j = 1 \\ & \lambda_j \geq 0 (j = 1,2,\cdots,n); S^+ \geq 0; S^- \geq 0 \end{cases} \quad (3)$$

In Eq. (3), λ_j indicates the combined weight of the decision unit DMU_j. φ indicates the relative efficiency of evaluation.

In the second stage, a System Failure Analysis (SFA) regression model is established to remove environmental factors and random noise so that all decision-making units are in the same environment. Frontier 4.1 software is used to analyze the impact of environmental variables on efficiency [23]. SFA can be evaluated according to Eq. (4).

$$S_{ij} = f(Z_j; \beta_i) + v_{ij} + \mu_{ij} \quad (4)$$

In Eq. (4), S_{ij} indicates input relaxation variables, Z_j represents environmental variables, β_i represents environmental variable coefficients, v_{ij} indicates random interference, and μ_{ij} indicates inefficient management.

In the third stage, the adjusted input index data is used instead of the original value, and the traditional DEA model is used again to measure the efficiency value. The calculated efficiency values exclude environmental factors and random disturbances [24].

2.4.2. DEA-Malmquist model and its decomposition

Assuming that the scale efficiency is constant, the Malmquist index can be decomposed into a technology efficiency change index and a technological progress index. Assuming that the scale efficiency is variable, the technical efficiency change index is further decomposed into a pure technical efficiency change index and a scaling efficiency change index. The DEA-Malmquist exponential model is based on efficiency and distance functions [25]. The Malmquist index is converted into a DEA-Malmquist index defined based on the efficiency function for efficiency measurement studies. The DEA-Malmquist index calculates the productivity change from the t period to the t+1 period, which avoids the differences caused by the period selection's arbitrariness and improves the model's identification ability. Assuming that there is $k = 1,2,\cdots,K$ decision unit DMUs. Each decision-making unit uses $n = 1,2,\cdots,N$ inputs $x_n^{k,t}$ in period $t = 1,2,\cdots,T$. Then, the $m = 1,2,\cdots,M$ yields $y_m^{k,t}$ is obtained. The total factor productivity (TFPch) is calculated according to Eq. (5).

$$\text{TFPch} = M(x^t, y^t, x^{t+1}, y^{t+1}) = (M_t \cdot M_{t+1})^{\frac{1}{2}} = \left(\frac{D_0^t(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)} \cdot \frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^{t+1}(x^t, y^t)}\right)^{\frac{1}{2}} \quad (5)$$

When the returns to scale remain constant, it is broken down into two parts: technology efficiency change (Effch) and technological progress change (Techch).

$$M(x^t, y^t, x^{t+1}, y^{t+1}) = \frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)} \times \left(\frac{D_0^t(x^{t+1}, y^{t+1})}{D_0^{t+1}(x^{t+1}, y^{t+1})} \cdot \frac{D_0^t(x^t, y^t)}{D_0^{t+1}(x^t, y^t)}\right)^{\frac{1}{2}} = Effch \times Techch \quad (6)$$

When the returns to scale are variable, the Effch can be decomposed into pure technical efficiency change (Pech) and scale efficiency change (Sech).

$$\text{Effch} = \frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)} = \frac{D_0^{t+1}(x^{t+1}, y^{t+1}|V)}{D_0^t(x^t, y^t|V)} \times \frac{D_0^{t+1}(x^{t+1}, y^{t+1}|C)/D_0^{t+1}(x^{t+1}, y^{t+1}|V)}{D_0^t(x^t, y^t|C)/D_0^t(x^t, y^t|V)} = \text{Pech} \times Sech \quad (7)$$

Ultimately, the Malmquist index comprises Techch, Pech, and Sech [26].

$$\text{TFPch} = \text{Techch} \times \text{Effch} = \text{Techch} \times \text{Pech} \times \text{Sech} \quad (8)$$

In the above equations, Pech stands for pure technology efficiency change index, Sech represents scale efficiency change index, and Techch represents technology progress index, indicating the degree of transition of the technical production boundary from t to t+1. (x^t, y^t) and (x^{t+1}, y^{t+1}) represent input and output vectors for the t and t+1 periods. D^t and D^{t+1} represent the returns to scale and variable distance functions for the t and t+1 periods.

2.4.3. Bootstrap-DEA method

The Bootstrap-DEA method is introduced for bias correction to accurately measure the environmental performance of pharmaceutical enterprises. The Bootstrap-DEA method calculates DEA efficiency based on numerical simulations of raw data to generate many simulated samples. The bias of the efficiency evaluation can be corrected to give confidence intervals for the efficiency evaluation [27]. The steps are as follows.

(1) The DEA model is used to measure the initial efficiency value $E_1, E_2 \cdots E_n$ on the original data.

(2) Sampling is carried out to obtain a Bootstrap sample $\alpha_1, \alpha_2 \cdots \alpha_n$ taking the initial efficiency value E_1, $E_2 \cdots E_n$ as the population.

(3) The Bootstrap sample α_1, $\alpha_2 \cdots \alpha_n$ is smoothed to get the smoothed sample α_1^0, α_2^0,$\cdots \alpha_n^0$. α_j^o is expressed as:

$$\alpha_j^o = \alpha_j + \frac{1}{\sqrt{1 + h^2/\delta_\alpha^2}}(\widetilde{\alpha_j^o} - \overline{\alpha_j^o}) \quad (9)$$

$\bar{\alpha}_j^0$ can be obtained according to Eq. (10).

$$\bar{\alpha}_j^0 = \frac{1}{s}\sum_{j=1}^{s} \alpha_j, \delta_\alpha^2 = \frac{1}{s}\sum_{j=1}^{s} (\alpha_j - \bar{\alpha})^2 \quad (10)$$

$\widetilde{\alpha_j^o}$ is obtained according to Eq. (11).

$$\tilde{\alpha}_j^0 = \begin{cases} \alpha_j + h\varepsilon_j, \\ 2 - \alpha_j - h\varepsilon_j \end{cases} \quad (11)$$

In Eq. (11), h is the smoothing parameter, and ε_j is the random error. Besides, $j = 1,2,\cdots s$.

(4) The initial efficiency value and the smoothed sample are used to adjust the data to obtain new data x_m^* and y_m^*, as expressed in Eq. (12)-Eq. (13).

$$x_m^* = \frac{E_m}{\alpha_m^0} x_m, \text{m=1,2,} \cdots n \quad (12)$$

$$y_m^* = \frac{E_m}{\alpha_m^*} y_m, m = 1,2,\cdots n \quad (13)$$

(5) The data in step four is measured by the DEA method to obtain the efficiency value φ_m^*.

(6) For each decision unit, repeat steps two to five to get the efficiency value φ_{mb}^*.

(7) For each decision unit, the Bootstrap corrected efficiency value $\tilde{\varphi}_m$ is calculated, as shown in Eq. (14).

$$\tilde{\varphi}_m = 2E_m - \frac{1}{B}\sum_{b=1}^{B} \varphi_{mb}^* \quad (14)$$

2.5. The Analysis Method of Influencing Factors of The Environmental Performance of Pharmaceutical Enterprises

2.5.1. Panel data Quantile Regression

Suppose there is a panel data model $y_{it} = x_{it}'\beta_i + \alpha_i +$

u_{it},$(i = 1,2,\cdots,N; t = 1,2,\cdots,T)$. u represents the random error term, β_i represents the coefficient of the explanatory variable, and α_i represents the random effect of the sample.

The Quantile Regression method is used to estimate the parameters of the above panel data model. The conditional quantile function [28] is established, as shown in Eq. (15).

$$Q(\tau \mid x_i, \beta(\tau)) = \alpha_i(\tau) + x_i'\beta(\tau)(i = 1,2,\cdots,N; t = 1,2,\cdots,T) \quad (15)$$

In Eq. (15), $x_i' = (x_{1i}, x_{2i}, \cdots, x_{ki})'$ is an explanatory variable, $\beta(\tau) = (\beta_1, \beta_2, \cdots, \beta_k)'$ is the coefficient vector under τ quantile. When τ moves on (0, 1), the parameter estimate of Quantile Regression on different quantile points can be obtained by solving to minimize the residual value. The minimized weighted absolute residuals are expressed in Eq. (16).

$$\hat{\beta} = \arg\min_{(\alpha,\beta)} \sum_{k=1}^{q} \sum_{i=1}^{N} \sum_{t=1}^{T} \omega_k \cdot \rho_{\tau_k}\left(y_{it} - \alpha_i - x_{it}'\beta(\tau_k)\right) \quad (16)$$

In Eq. (16), ω_k is the weight coefficient corresponding to each quantile.

2.5.2. Review Quantile Regression

The review Quantile Regression model is proposed by combining the review regression model with quantiles [29], as demonstrated in Eq. (17).

$$Q_n(\beta; \theta) = \min_{\beta_\theta} \frac{1}{N} \sum_{i=1}^{N} \left[\left\{\theta - I(y_i < max\{0, x_i'\beta_\theta\})\right)(y_i - max\{0, x_i'\beta_\theta\})\right] \quad (17)$$

In Eq. (17), $I(y_i < max\{0, x_i'\beta_\theta\})$ is the characteristic function. Quantile Regression and review regression are combined to study the influencing factors of review Quantile Regression on the environmental performance of pharmaceutical enterprises.

2.5.3. Selection of variables influencing environmental performance

It is analyzed from two aspects: internal and external influencing factors, as shown in Fig. 4.

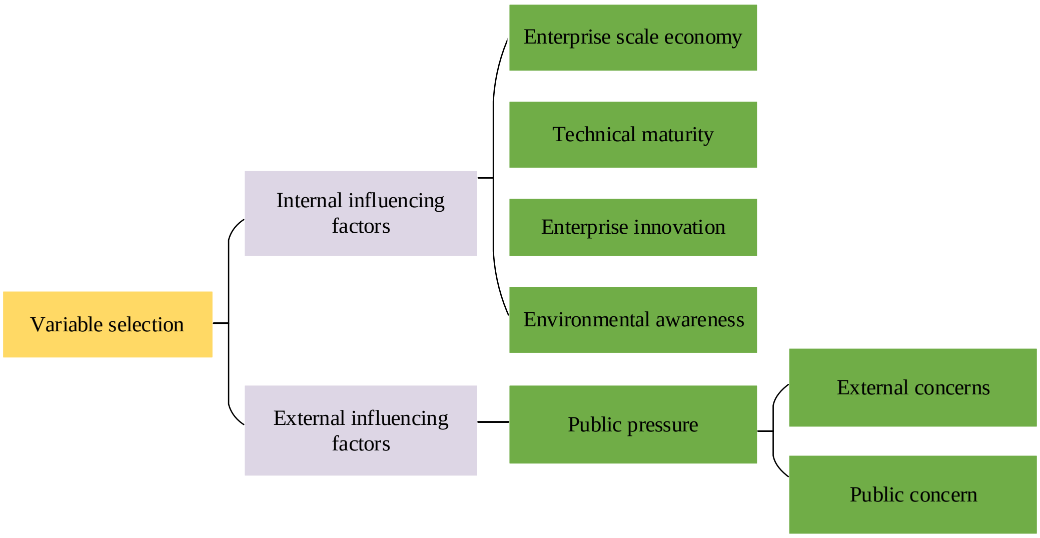

Figure 4. Selection of variables influencing the environmental performance of pharmaceutical enterprises

As shown in Fig. 4, internal factors include economies of scale, technological maturity, innovation, and environmental awareness. External influences include public pressure. Enterprises achieving economies of scale can promote technological progress, reduce costs, and increase labor productivity from their perspective. Then, enterprises can obtain more profits, become bigger and stronger, and continuously enhance their competitiveness. The maturity of technology is mainly reflected in the R&D capital investment of enterprises. Enterprise innovation is mainly technological innovation ability. External factors are mainly public pressure, mainly involving external attention and public concern.

2.5.4. Panel quantile and review Quantile Regression models of environmental performance influencing factors

A panel Quantile Regression model of the influencing factors of the environmental performance of pharmaceutical enterprises is constructed. The panel regression model is constructed with environmental efficiency as the dependent variable and economies of scale (scale), technology maturity (tech), business innovation (inn), environmental awareness (env), and public stress (stress) as independent variables.

$$\text{Efficiency}_{it} = c + \alpha_1 \text{ scale}_{it} + \alpha_2 \text{ tech}_{it} + \alpha_3 \text{ inn}_{it} + \alpha_4 \text{ env}_{it} + \alpha_5 \text{ stress}_{it} + \varepsilon_i \quad (18)$$

In Eq. (18), $i = 1,2, \cdots 100$. c represents the constant term of the regression equation. α_1, α_2, α_3, α_4, and α_5 indicate the regression coefficients of each index. ε_i represents the error term. Efficiency_{it} indicates the environmental efficiency value of the ith enterprise in the tth year. Quantile Regression is operated using R software.

A review Quantile Regression model is represented in Eq. (19).

$$\text{efficiency}_{it} = max(0, c + \alpha_1 \text{ scale}_{it} + \alpha_2 \text{ tech}_{it} + \alpha_3 \text{ inn}_{it} + \alpha_4 \text{ env}_{it} + \alpha_5 \text{ stress}_{it} + \varepsilon_i) \quad (19)$$

In Eq. (19), $i = 1,2,\cdots 100$.

2.6. Data Processing

For the environmental performance evaluation index system of pharmaceutical enterprises, the panel data of 100 pharmaceutical enterprises in China is used as the research object to analyze the environmental performance of pharmaceutical enterprises. The data comes from the enterprise's annual reports, enterprise social responsibility reports, environmental reports published on the enterprise's official website, and data released by the environmental protection bureau where the enterprise is located. The DEA software DEAP2.1 calculates the data. There are many sample data, so it is not convenient for all enterprises to display them. At present, only 15 pharmaceutical enterprises have demonstrated complete information on their environmental performance.

3. Enterprise Environmental Performance Evaluation and Influencing Factors Analysis

3.1. Measurement Results and Analysis Based on the DEA-Malmquist Method

According to the index system, the environmental performance of enterprises from 2015 to 2020 is evaluated and analyzed. The environmental performance of 15 pharmaceutical enterprises is listed. The dynamic change of environmental performance every two years is a result, as revealed in Fig. 5.

Number	Variable	2015-2016	2017-2018	2019-2020
1	Aohong Pharmaceutical	3.734	2.752	1.375
2	Baiyunshan	1.213	1.135	0.716
3	Dong'e donkey hide gelatin	0.847	0.589	1.145
4	Fosun Pharma	0.439	1.189	0.852
5	Hisun Pharm	0.736	1.154	3.199
6	China Resources Sanjiu	0.855	0.596	1.151
7	Kelun Pharmaceutical	1.187	0.786	1.235
8	Ma Yinglong	2.149	0.282	1.849
9	Newsummit	1.609	1.745	1.269
10	Modern pharmacy	0.922	1.325	1.989
11	Shanghai Pharmaceutical	1.195	0.967	1.112
12	Qizheng Tibetan Medicine	1.066	0.357	2.334
13	Yaoyou Shares	0.556	1.258	0.986
14	Yunnan Baiyao	0.992	0.856	1.133
15	Zhengda tianqing	1.501	1.112	1.489

Figure 5. Dynamic environmental performance of pharmaceutical enterprises

From Fig. 5, the first column is the change in the environmental performance of pharmaceutical enterprises from 2015 to 2016, with an increase greater than one and a decrease less than one. An equal to one indicates no upward or downward trend. From the above data, there are still specific differences in environmental performance between enterprises.

3.2. Analysis of Dynamic Changes in The Environmental Performance of Pharmaceutical Enterprises

Malmquist exponential decomposition is used to analyze the dynamics of the environmental performance of pharmaceutical enterprises from 2015 to 2020. The environmental performance of pharmaceutical enterprises is divided into the Techch, the Pech, and the Sech. Techch reflects the technical level of DMU, Pech reflects DMU's utilization of resources, Sech reflects the scale state of DMU, and Effch combines the scale efficiency index and pure technical efficiency index to comprehensively reflect the management organization level of DMU. The results of the evaluation are given in Fig. 6.

Number	Enterprise	*effch*	*techch*	*pech*	*sech*	*Malmquist index*
1	Aohong Pharmaceutical	1	1.692	1	1	1.692
2	Baiyunshan	0.984	1.053	0.992	0.992	1.038
3	Dong'e donkey hide gelatin	1	0.966	1	1	0.966
4	Fosun Pharma	0.886	1.019	0.872	1.017	0.902
5	Hisun Pharm	1.279	1.125	1.157	1.107	1.437
6	China Resources Sanjiu	0.796	1.071	0.805	0.991	0.852
7	Kelun Pharmaceutical	0.637	1.124	0.868	0.734	0.717
8	Ma Yinglong	1.482	1.498	1.475	1.007	2.219
9	Newsummit	1.818	1.152	2.115	0.862	2.094
10	Modern pharmacy	1.086	1.073	1.098	0.988	1.173
11	Shanghai Pharmaceutical	1	1.058	1	1	1.058
12	Qizheng Tibetan Medicine	0.871	1.205	1	0.866	1.051
13	Yaoyou Shares	1.817	1.328	1.477	1.235	2.418
14	Yunnan Baiyao	1	1.091	1	1	1.095
15	Zhengda tianqing	1.205	1.069	1.199	1	1.303

Figure 6. Dynamic evaluation results of the environmental performance of pharmaceutical enterprises

From Fig. 6, from the perspective of the technical efficiency index, the average technical efficiency index of pharmaceutical enterprises is 1.224, an average increase of 2.6%. The technical efficiency index of most enterprises is greater than 1, indicating that most enterprises have a good level of management organization and promote environmental performance. It also shows that China's pharmaceutical enterprises have gradually acquired the ability to transform technology into commercial products. From the pure technical efficiency index, the average pure technical efficiency of pharmaceutical enterprises is 1.447, an average increase of 4.9% in five years. From the scale efficiency index, the average value of Sech is 1.005. Efficiency at scale has declined by an average of 2.5% over five years. The existing size of the enterprise hinders the improvement of the enterprise's environmental performance to some extent.

3.3. Bootstrap-DEA Model Measurement Results and Analysis

3.3.1. Stability verification of the Bootstrap method

The Bootstrap-DEA method is introduced to correct environmental performance. The number of iterations is set to 1000, 2000, and 3000 to verify the stability of the Bootstrap method, respectively, as shown in Fig. 7.

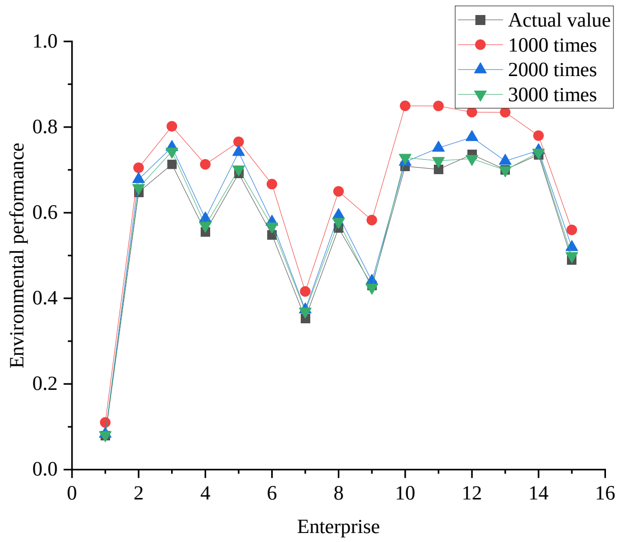

Figure 7. Stability verification of the Bootstrap method

It is found that the number of iterations exceeds 3,000. The estimated results are very different from the actual results, so the number of iterations is selected as 3,000.

3.3.2. Analysis of Bootstrap-DEA model estimation efficiency values

R software is used to analyze relevant index data, taking 2020 as an example. The results of the efficiency values estimated by Bootstrap-DEA are presented in Fig. 8.

Number	Enterprise	Efficiency value	Correction value	Lower limit	Upper limit	Deviation
1	Aohong Pharmaceutical	0.2891	0.2271	0.1255	0.2802	0.0122
2	Baiyunshan	1	0.6245	0.5339	0.9218	0.3755
3	Dong'e donkey hide gelatin	1	0.6112	0.5226	0.9114	0.3812
4	Fosun Pharma	0.1721	0.1104	0.0931	0.1577	0.0613
5	Hisun Pharm	0.1785	0.1275	0.1045	0.1688	0.0422
6	China Resources Sanjiu	0.4647	0.3115	0.2619	0.4251	0.1501
7	Kelun Pharmaceutical	0.637	0.0675	0.0556	0.0896	0.0277
8	Ma Yinglong	0.9533	0.6097	0.5194	0.9257	0.3805
9	Newsummit	0.0752	0.0509	0.0419	0.0688	0.0233
10	Modern pharmacy	0.2892	0.1899	0.1578	0.2633	0.0767
11	Shanghai Pharmaceutical	1	0.6078	0.5193	0.8874	0.3856
12	Qizheng Tibetan Medicine	1	0.6125	0.5249	0.9088	0.3689
13	Yaoyou Shares	1	0.6126	0.5185	0.9311	0.3765
14	Yunnan Baiyao	0.7452	0.6926	0.5524	0.7155	0.0578
15	Zhengda tianqing	1	0.6119	0.5212	0.9335	0.3477

Figure 8. Estimated efficiency value of Bootstrap-DEA

From Fig. 8, from uncorrected environmental efficiency values, nearly half of all enterprises are at the forefront of production yearly. From the confidence interval for environmental performance given by Bootstrap-DEA, the original environmental performance value is minimal in the confidence interval. Using the original efficiency value to evaluate the environmental performance between enterprises may be incorrect. It cannot be used to evaluate the difference in environmental performance between enterprises.

The environmental performance of pharmaceutical enterprises from 2015 to 2020 is shown in Fig. 9.

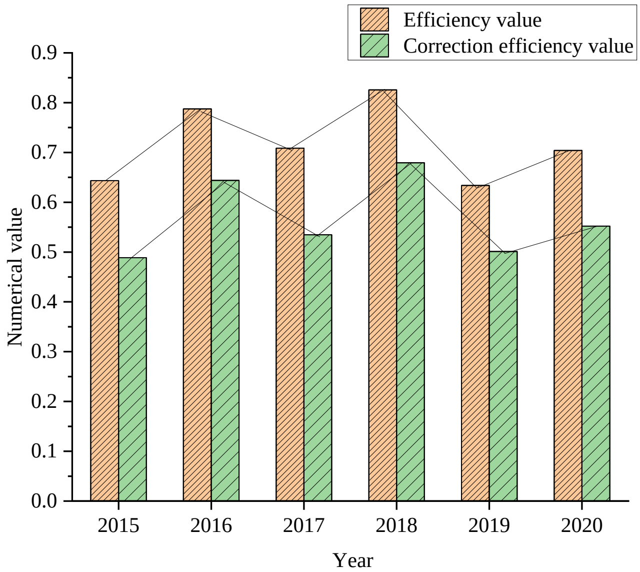

Figure 9. Environmental performance of pharmaceutical enterprises from 2016 to 2020

From Fig. 9, the results of the uncorrected efficiency value and revised efficiency value show that the mean value of the environmental performance of China's pharmaceutical industry shows a wave change trend. The energy conservation and emission reduction work of pharmaceutical enterprises has been effective. The environmental performance value after the correction has been significantly reduced.

3.3.3. Statistical description of the environmental performance of pharmaceutical enterprises

The corrected efficiency value is used for calculation, as shown in Fig. 10.

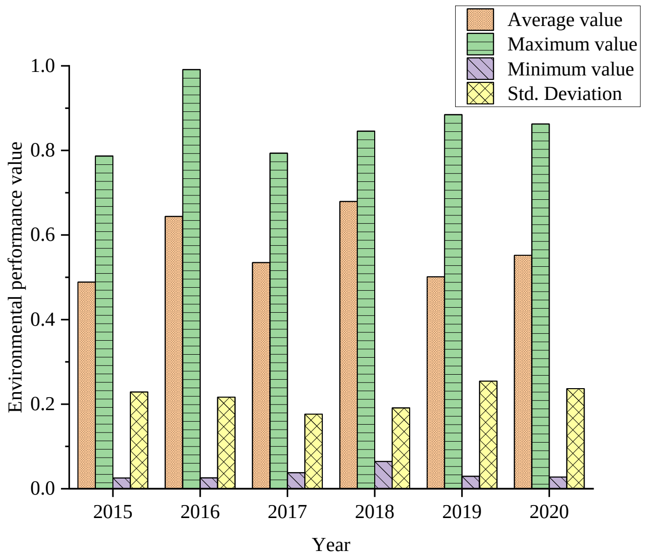

Figure 10. Statistical description of the environmental performance of pharmaceutical enterprises

Fig. 10 shows that the level of environmental performance of Chinese pharmaceutical enterprises is generally not high. Most enterprises have much room to improve their environmental performance. Most enterprises have a weak awareness of environmental protection. Some enterprises only pay attention to economic benefits, and the environmental protection technology of enterprises is backward. At present, Chinese pharmaceutical enterprises are still a model of high input, high consumption, high pollution, and high emissions. The maximum and minimum environmental performance of pharmaceutical enterprises differ significantly, indicating a large gap in environmental performance between pharmaceutical enterprises in China. However, there is an overall trend toward progress.

3.4. Analysis of Influencing Factors of The Environmental Performance of Pharmaceutical Enterprises

3.4.1. Series fluctuations in exchange rate yields in the Association of Southeast Asian Nations

R software is used to perform an empirical inspection to avoid model setting errors. First, the F-test is used to decide whether to use a mixed or fixed-effect model. The Hausman test is then used to determine whether a random or fixed-effect model should be established. Fig. 11 reveals the results.

Index	Mixing effect Coef	Fixed effect
scale	1.1862*	1.5535**
tech	-1.0344**	2.3655*
env	9.5978**	8.3321 ***
inn	8.7133	1.3588**
stress	6.7425*	1.3346*
Adj R-squared	0.5028	0.5113
F	1.1103	4.0785
Prob.F	0.0065	0.0003

*** p<1%, ** p<5%, * p<10%

Figure 11. Mixed-effect and fixed-effect model regression results

From Fig. 11, The R^2 of the fixed-effect model of environmental performance influencing factors is 0.5113. Explanatory variables explain 51% of the change in environmental performance. Compared with the mixed model, the fixed-effect model has a better fit, indicating that the selected variables are more comprehensive. The impact on the environmental performance of the enterprise is better explained when considering individual heterogeneity.

R software is used to perform the F test. The value of the F statistic is 4.0785, and the corresponding P value is 0.0003. It is believed that there is an individual fixed effect, so the fixed effect model is chosen. Then, random-effects significance tests are performed to make choices between fixed-effect and random-effects models. The Hausman test is performed using R software. The P value is 0.002, so the null hypothesis is rejected. A fixed-effect model should be used.

3.4.2. Quantile Regression analysis of factors influencing environmental performance

All quantile estimates of the respective variables are obtained using R software. Besides, scale is for economies of scale, tech for technology maturity, inn for corporate innovation, env for environmental awareness, and stress for public pressure, as shown in Fig. 12.

φ	Constant term	*scale*	*tech*	*inn*	*env*	*stress*
0.1	0.9025	-0.6674***	0.2004	0.1255***	0.6788***	0.3477***
0.2	6.2991***	0.4728 **	-0.8578***	0.5422***	0.7492***	0.2188 **
0.3	7.7392***	0.8894***	-1.2422***	0.4311*	0.6533***	0.1233***
0.4	6.0672 **	0.7526*	-0.9811 **	0.2245***	0.4222	0.1822 **
0.5	6.6351***	0.8821***	-1.0622***	0.3421***	0.6692***	0.3007***
0.6	4.2866***	0.6544	-0.6922***	0.0324***	0.6301***	0.1502*
0.7	0.2826*	0.1223***	-0.0998***	0.2457 **	0.1688***	0.4777***
0.8	-0.1803	0.0522 **	-0.0388*	0.2319	0.0432 **	0.0286***
0.9	-0.3267***	0.0245***	-0.1499	0.1266***	0.0211***	0.0177***

*** p<1%, ** p<5%, * p<10%

Figure 12. Quantile Regression results of factors influencing environmental performance

From Fig. 12, the constant term is the enterprise's environmental performance level when it does not take any environmental protection measures. The results of Quantile Regression show that if an enterprise does not take any environmental protection measures, it can initially rely on nature's self-decomposition (at the 10% and 30% quantile levels). The environmental performance level of the enterprise can still reach a good level. Over time, the load on nature becomes heavier and heavier. The level of the environmental performance of the enterprise must decline accordingly. The impact coefficient of enterprise economies of scale on enterprise environmental performance is positive, indicating that enterprise-scale has a pulling effect on enterprise environmental performance. A higher φ value indicates a higher level of environmental performance for the enterprise. The larger the enterprise, the higher the level of environmental performance. For the Quantile Regression results of enterprise technology maturity, the coefficient of enterprise technology maturity is negative. The lower the technology level, the worse the environmental performance level of the enterprise. The environmental awareness of enterprises, the innovation ability of enterprises, and the public pressure of enterprises all have positive promotion effects on the impact of enterprises' environmental performance.

3.4.3. Review Quantile Regression result analysis

The results of the review Quantile Regression analysis of the factors influencing the environmental performance of pharmaceutical enterprises are demonstrated in Fig. 13.

φ	Constant term	*scale*	*tech*	*inn*	*env*	*stress*
0.1	0.9522	-0.6974***	0.2404	0.1315***	0.6905***	0.3607***
0.2	6.4277***	0.4928 **	-0.8778***	0.5652***	0.7652***	0.2308 **
0.3	7.5614***	0.9194***	-1.2622***	0.4412*	0.6813***	0.1451***
0.4	6.0672 **	0.7526*	-0.9811 **	0.2245***	0.4222	0.1822 **
0.5	6.6351***	0.8821***	-1.0622***	0.3421***	0.6692***	0.3007***
0.6	4.2866***	0.6544	-0.6922***	0.0324***	0.6301***	0.1502*
0.7	0.2826*	0.1223***	-0.0998***	0.2457 **	0.1688***	0.4777***
0.8	-0.1803	0.0522 **	-0.0388*	0.2319	0.0432 **	0.0286***
0.9	-0.3267***	0.0245***	-0.1499	0.1266***	0.0211***	0.0177***

*** p<1%, ** p<5%, * p<10%

Figure 13. Review Quantile Regression results of factors influencing environmental performance

As shown in Fig. 13, the size of an enterprise has a pulling effect on its environmental performance of an enterprise. The larger the enterprise, the higher the level of environmental performance. Increasing the size of pharmaceutical enterprises can narrow the gap between enterprises' environmental performance levels. Environmental awareness plays a significant role in improving the environmental efficiency of enterprises. Additionally, the impact of enterprises' innovation ability and public pressure on enterprise environmental performance has a positive driving effect. It is not significant at minority quantiles. It is suggested that the government should increase support for enterprises' technology R&D and encourage enterprises to continuously promote their scale and technological innovation capabilities to improve pharmaceutical enterprises' environmental information disclosure mechanism.

4. Conclusion

The rapid development of China's pharmaceutical industry has brought considerable benefits to society and great tests to the environment. With the development of a green economy, environmental performance evaluation plays a vital role in continuously improving pharmaceutical enterprises' environmental performance and promoting enterprises' innovation and development. It is essential to study a scientific and operable environmental performance evaluation system. Here, the panel data of 100 pharmaceutical enterprises in China from 2015 to 2020 is used as the research object. The BMDEA model is constructed based on the three-stage DEA model. The Bootstrap-DEA method is introduced to correct the environmental performance values and build an index evaluation system. Panel Quantile Regression and review Quantile Regression are used to analyze the influencing factors of the environmental performance of pharmaceutical enterprises. The results show that there are differences in environmental performance among pharmaceutical enterprises. The average value of the technical efficiency index of pharmaceutical enterprises is about 1.224, an average increase of 2.6%, indicating that most enterprises have a good level of management organization and promote environmental performance. From the pure technical efficiency index perspective, pharmaceutical enterprises' average pure technical efficiency is 1.447. The technical level has increased by about 4.9%. Pharmaceutical enterprises have improved their use of resources. The average size efficiency index is 1.005, a decrease of about 2.5%. The existing size of the enterprise hinders the improvement of the enterprise's environmental performance to some extent. The influencing factors of pharmaceutical enterprises are analyzed by the Quantile Regression method. It is found that the impact of enterprise economies of scale, technological maturity, environmental awareness and public pressure, and enterprise innovation on improving corporate environmental performance have a significant promoting effect on most quantiles but not in minority quantiles. It is suggested that pharmaceutical enterprises should continuously enhance their scale and focus on improving their innovation capabilities. Furthermore, enterprises should increase investment in environmental protection, continuously promote advanced environmental management systems, and improve the incentive mechanism for enterprise environmental performance assessment. This work aims to improve the environmental performance of pharmaceutical enterprises and guide them to improve their innovation capabilities. The downside is that environmental performance evaluation indexes need to be continuously improved. Follow-up research will continue to improve the index system and evaluation method of environmental performance evaluation.

References

[1] Benzidia S, Makaoui N, Bentahar O. The impact of big data analytics and artificial intelligence on green supply chain process integration and hospital environmental performance. Technological Forecasting and Social Change, 2021, 165: 120557.

[2] Asif K. The Impact of Procurement Strategies on Supply Chain Sustainability in the Pharmaceutical Industry. South Asian Journal of Social Review, 2022, 1(1): 53-64.

[3] Xu J, Wang X, Liu F. Government subsidies, R&D investment and innovation performance: analysis from pharmaceutical sector in China. Technology Analysis & Strategic Management, 2021, 33(5): 535-553.

[4] Peng J, Song Y, Tu G, et al. A study of the dual-target corporate environmental behavior (DTCEB) of heavily polluting enterprises under different environment regulations: Green innovation vs. pollutant emissions. Journal of Cleaner Production, 2021, 297: 126602.

[5] Yang M, Bento P, Akbar A. Does CSR influence firm performance indicators? Evidence from Chinese pharmaceutical enterprises. Sustainability, 2019, 11(20): 5656.

[6] López-Toro A A, Sánchez-Teba E M, Benítez-Márquez M D, et al. Influence of ESGC indicators on financial performance of listed pharmaceutical companies. International Journal of Environmental Research and Public Health, 2021, 18(9): 4556.

[7] Qomariah N, Nursaid E B S. Improving financial performance and profits of pharmaceutical companies during a pandemic: Study on environmental performance, intellectual capital and social responsibility. Access Success, 2021, 22: 154-165.

[8] Nguyen T. The effect of internal control on the performance of pharmaceutical firms in Vietnam. Accounting, 2021, 7(2): 395-400.

[9] Yang L, Qin H, Gan Q, et al. Internal control quality, enterprise environmental protection investment and finance performance: An empirical study of China's a-share heavy pollution industry. International Journal of Environmental Research and Public Health, 2020, 17(17): 6082.

[10] Yang L, Tan J, Xia W, et al. Corporate Performance, Market-Industry Competition and Enterprise Environmental-Protection Investment. Sustainability, 2022, 14(9): 5459.

[11] JosephNg P S, Eaw H C. Making financial sense from EaaS for MSE during economic uncertainty. Future of Information and Communication Conference. Springer, Cham, 2021: 976-989.

[12] Li L, Zhang J. Research and analysis of an enterprise E-commerce marketing system under the big data environment. Journal of Organizational and End User Computing (JOEUC), 2021, 33(6): 1-19.

[13] Liu R, He F, Ren J. Promoting or inhibiting? The impact of enterprise environmental performance on economic performance: Evidence from China's large iron and steel enterprises. Sustainability, 2021, 13(11): 6465.

[14] Cao Y, Bian Y. Improving the ecological environmental performance to achieve carbon neutrality: The application of DPSIR-Improved matter-element extension cloud model. Journal of Environmental Management, 2021, 293: 112887.

[15] Achi A, Adeola O, Achi F C. CSR and green process innovation as antecedents of micro, small, and medium enterprise performance: Moderating role of perceived environmental volatility. Journal of Business Research, 2022, 139: 771-781.

[16] Wen H, Lee C C, Song Z. Digitalization and environment: how does ICT affect enterprise environmental performance. Environmental Science and Pollution Research, 2021, 28(39): 54826-54841.

[17] Zhang Y, Zhao Y, Sun W, et al. Ocean wave energy converters: Technical principle, device realization, and performance evaluation. Renewable and Sustainable Energy Reviews, 2021, 141: 110764.

[18] Omrani H, Alizadeh A, Emrouznejad A, et al. A robust credibility DEA model with fuzzy perturbation degree: An application to hospitals performance. Expert Systems with Applications, 2022, 189: 116021.

[19] Zhang C, Chen P. Applying the three-stage SBM-DEA model to evaluate energy efficiency and impact factors in RCEP countries. Energy, 2022, 241: 122917.

[20] Cova-Alonso D J, Díaz-Hernández J J, Martínez-Budría E. A strong efficiency measure for CCR/BCC models. European Journal of Operational Research, 2021, 291(1): 284-295.

[21] Zhou Z, Zachariah A, Conathan D, et al. Assessing Resource-Performance Trade-off of Natural Language Models using Data Envelopment Analysis. arXiv preprint arXiv:2211.01486, 2022.

[22] Xu X, Pan L C, Ni Q H, et al. Eco-efficiency evaluation model: a case study of the Yangtze River Economic Belt. Environmental monitoring and assessment, 2021, 193(7): 1-22.

[23] Wang Q, Wang J, Li H, et al. Research on financing efficiency and influencing factors of equipment manufacturing industry——Regression model based on SFA panel data. Journal of Intelligent & Fuzzy Systems, 2021, 40(4): 8117-8126.

[24] Moutinho V, Madaleno M, Macedo P. The effect of urban air pollutants in Germany: eco-efficiency analysis through fractional regression models applied after DEA and SFA efficiency predictions Sustainable Cities and Society, 2020, 59: 102204.

[25] Lu X, Xu C. The difference and convergence of total factor productivity of inter-provincial water resources in China based on three-stage DEA-Malmquist index model. Sustainable Computing: Informatics and Systems, 2019, 22: 75-83.

[26] Zheng Z. Energy efficiency evaluation model based on DEA-SBM-Malmquist index. Energy Reports, 2021, 7: 397-409.

[27] Koçak E, Kınacı H, Shehzad K. Environmental efficiency of disaggregated energy R&D expenditures in OECD: a bootstrap DEA approach. Environmental Science and Pollution Research, 2021, 28(15): 19381-19390.

[28] Bilgili F, Ozturk I, Kocak E, et al. The nexus between access to electricity and CO2 damage in Asian Countries: The evidence from quantile regression models. Energy and Buildings, 2022, 256: 111761.

[29] Guo L, Liu K, Song Y, et al. Recovering hotel room sales during the COVID-19 pandemic: lessons from OTA information using the quantile regression approach. Current Issues in Tourism, 2022, 25(1): 94-114.