Operational Performance Evaluation of Iron and Steel Industry in China under the Background of Digital Transformation – An Application of Data Envelopment Analysis

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Abstract. This paper aims to study the operating performance of iron and steel enterprises under the background of digital transformation, using the DEA-Malmquist model to carry out static and dynamic analysis of the data from 2018 to 2022, which is divided into four parts. Generally speaking, most of the selected companies have good operational performance, but there is still room for improvement. This paper aims to establish a more comprehensive and objective evaluation system that aligns with the actual development of the steel industry, in order to fulfill the operational performance assessment needs of listed steel enterprises within the context of digitalization.

Keywords: Iron and Steel Industry, DEA model, Operational performance.

1. Introduction

Industry 4.0 serves as a pivotal gateway for the complete integration of the Internet into production and manufacturing systems, leveraging an intelligent interconnection system to gather data tailored to specific features and personalized requirements [1]. This data is then utilized by an intelligent manufacturing system to fabricate customized products. Given the emergence of advanced artificial intelligence (AI) systems, it becomes imperative for the steel industry to enhance its production processes while simultaneously expanding capacity. The steel manufacturing process is a highly intricate, dynamic, and integrated system that encompasses multiple factors, scales, units, and levels of integration. It represents the holistic amalgamation of various components rather than a mere summation. Steel Industry 4.0 signifies the realization of nearly fully automated and intelligent production in the steel sector where operators, products, and production equipment are seamlessly interconnected through the Internet of Things (IoT). A vast volume of data is captured by sensors which are then processed by artificial intelligence to optimize production lines, fostering substantial synergies among diverse devices. It is essential to conduct comprehensive research on the integration mode and implementation strategy of the iron and steel industry with Industry 4.0 to achieve precise manufacturing, refined management, intelligent decision-making, and optimized operation within the iron and steel sector through innovative thinking, mechanisms, modes, and technologies as the core components.

Currently, the iron and steel industry, particularly China's iron and steel sector, is confronted with challenges pertaining to excessive production capacity, supply-demand imbalance, and inadequate structural composition. It is essential to conduct thorough research on the integration mode and implementation strategy of Industry 4.0 in order to achieve precision manufacturing, refined management, intelligent decision-making, and optimized operations within the iron and steel sector. This necessitates innovative thinking, mechanisms, models, and technologies as the core drivers for accomplishing these objectives in a manner that aligns with the rigorous standards set by Nature journal.

The digital transformation of the iron and steel industry fundamentally entails the reconstruction of productivity and production relations. It involves leveraging digital technology to empower, restructure organizational processes, culture, and enhance both internal and external capacities of

enterprises. The significance of enterprise development in this context is self-evident [2]. It can be seen that the digital transformation of the steel industry has made an important contribution to the sustained, stable and healthy development of the Chinese national economy. Since the 18th National Congress of the Communist Party of China, the integration and development of digital technologies such as 5G and industrial Internet with the steel industry has been accelerating [3]. In summary, it is of great practical significance to study the operating performance of the steel industry under the background of digital transformation.

2. Literature review

In recent years, domestic scholars have made a lot of explorations on how to improve operating efficiency. Li Kangziyi studied the performance of 71 listed IT companies in China, and found the problems existing in the development of the information technology industry [4]. Zhan Yanling selected more than 40 listed coal companies in China, studied their financing efficiency through the DEA method, and put forward corresponding suggestions given the shortcomings [5]; Wang Junling and Xu Danning took China's iron and steel industry as the research object [6], and put forward relevant policies and suggestions from the production efficiency and input redundancy from 2009 to 2016. Shu Huan and Hong Wei analyzed the social responsibility efficiency of 16 construction enterprises classified by the Securities Exchange from 2012 to 2016[7], and explored the reasons affecting the change in comprehensive efficiency; Li Qian and Liu Bingjie analyzed the efficiency level and change trend of information transmission[8], software and information technology companies from both horizontal and vertical perspectives, and found that the main reason for the decline in corporate efficiency was the decline in technical efficiency. Domestic scholars focus more on solving the problem of low operating efficiency of listed companies at the micro level but lack sorting out and analyzing the performance problems existing in the secondary industry from the macro perspective.

As for the performance evaluation of the iron and steel industry, some scholars used data envelopment analysis (DEA) to conduct a dynamic evaluation of a certain iron and steel enterprise in the early stages. This method can make up for the defects of financial index evaluation and principal component analysis methods, and the evaluation results by the DEA method can objectively reflect the efficiency of listed companies in the steel industry and provide decision-making reference for their management, but the research lacks comparison with other steel enterprises. Some scholars use CCR and G2GS2 in the DEA method to measure the input-output efficiency of 23 listed companies in China's iron and steel industry in 2003-2004. The research results show that the overall comprehensive efficiency of listed companies in China's iron and steel industry is not high, and some enterprises have not yet reached an effective economic scale. However, the study is a static process, which does not make an objective evaluation of the dynamic development of China's iron and steel industry. Scholars Cha Hongwang and CAI Gaolou used the BBC model in the DEA method to evaluate and study the innovation performance of 32 big data enterprises in 2015[9]. According to the research results, the innovation efficiency of China's big data enterprises is low on the whole, among which the input of innovation factors is small, the pure technical efficiency is at a low level, and the input of big data enterprises has not yet achieved the optimal output.

These studies provide evidence that the DEA approach serves as a robust method for assessing firm performance. This paper refers to previous scholars' research and uses the DEA and Malmquist index model for operational evaluation of the sample companies under the background of digital transformation, as well as analyze the existing problems in the digital transformation process of the Chinese iron and steel industry. It evaluates the operational performance from two perspectives: static and dynamic. In the end, some suggestions are put forward to improve the operational performance while in the implementation of digital transformation.

3. Methodology

3.1. Data envelopment analysis model

The DEA production frontier is formulated through the application of linear programming techniques, resulting in a piece-wise linear boundary that encompasses the input and output data observed [10]. Charnes, Cooper, and Rhodes were the pioneers in proposing the DEA methodology as an assessment tool for decision-making units [11]. DEA has been effectively utilized as a tool for performance assessment across various sectors, including manufacturing, education, finance, healthcare and small business development. Seiford offers a comprehensive bibliography of DEA applications. By conducting a comprehensive analysis of the input-output ratio, this study utilizes the weight of each input and output index of DMU as a variable to assess operational effectiveness and determine the efficiency of each DMU. Simultaneously, the projection method can be utilized to identify the factors contributing to non-DEA efficient or weak DEA effective DMU and suggest the direction and extent of enhancement.

In the DEA model, it is assumed that there are n DMUs, and each DMU_j has m types of input (representing "resource consumption") and s types of output (representing the amount of information indicating "effectiveness" after consuming "resource"). x_{ij} represents the total input of the DMU_j to type i, y_{rj} represents the output of the department j to type r, v_i represents the weight of type i input, u_r represents the weight of type r output, where $x_{ij}>0$, $y_{rj}>0$, $v_i>0$, $u_r>0$ (i=1, 2..., m; R = 1, 2..., s; J = 1, 2…, n). For the weight coefficient v= (v_1, v_2..., v_m) 'and u= (u1, u2..., us) ', each DMU_j has a corresponding number of evaluation indicators. The weights v and u are appropriately selected so that $h_j \leq 1$.

$$h_j = \sum_{r=1}^{s} u_r y_{rj} / \sum_{i=1}^{m} v_i x_{ij} \tag{1}$$

Now the BCC model is adopted for the efficiency evaluation of DMU_{j0} is carried out.

$$\boldsymbol{\varphi} = max \sum_{r=1}^{s} u_r y_{rj_0} + c_0$$
$$(BCC) s.t. \begin{cases} \sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} - c_0 \geq 0, \forall j \in \boldsymbol{N}, \\ \sum_{i=1}^{n} v_i x_{ij_0} = 1, \\ u_r \geq 0, \forall r = 1, \cdots, s \\ v_i \geq 0, \forall i = 1, \cdots, m \end{cases} \tag{2}$$

In formula (2), N indicates a total of n DMUs. The BCC model adds a fixed variable c_0 to the traditional CCR model to allow variable returns to scale. The effectiveness of DMU $_{j0}$ is evaluated about all other DMUs. If v*>0, u*>0 exists in the optimal solution obtained by solving this linear program, and the corresponding target value φ*=1, then the j0 decision unit is said to be DEA efficient, otherwise it is DEA inefficient.

3.2. Malmquist index model

The Malmquist index was initially introduced by the Swedish economist Malmquist in 1953 [12]. In 1982, Caves pointed out that the Malmquist index can be used to represent the input-based total factor productivity index (TFP index) under multi-input and output conditions. Later, Fare combined the Malmquist index with the traditional DEA model to measure TFP. At present, the Malmquist index measurement method based on DEA has been widely used in the measurement of total factor productivity in various fields. From period t to period t+1, its calculation formula is as follows:

$$M_0(x_{t+1}, y_{t+1}, x_t, y_t) = \left[\frac{d_0^t(x_{t+1}, y_{t+1})}{d_0^t(x_t, y_t)} \times \frac{d_0^{t+1}(x_{t+1}, y_{t+1})}{d_0^{t+1}(x_t, y_t)} \right]^{1/2} \tag{3}$$

$M_0(x_{t+1}, y_{t+1}, x_t, y_t)$ is the Malmquist total factor productivity index, (x_t, y_t), (x_{t+1}, y_{t+1}) represents the input and output vectors for periods t and t+1 respectively; $d_0^t(x_t, y_t)$, $d_0^{t+1}(x_t, y_t)$ represent the distance function referenced by t and t+1 periods technology respectively.

Assuming constant returns to scale, the Malmquist total factor productivity index can be decomposed into the technology efficiency change index (TE) and technology Progress index (TP), as follows:

$$M_0(x_{t+1}, y_{t+1}, x_t, y_t) = \frac{d_0^{t+1}(x_{t+1}, y_{t+1})}{d_0^t(x_t, y_t)} \times \left[\frac{d_0^t(x_{t+1}, y_{t+1})}{d_0^{t+1}(x_{t+1}, y_{t+1})} \times \frac{d_0^t(x_t, y_t)}{d_0^{t+1}(x_t, y_t)}\right]^{1/2} = TE \times TP \quad (4)$$

In 1994, Fare further decomposed total efficiency (TE) into pure technical efficiency change (PTE) and scale efficiency change (SE) to reveal the impact of scale efficiency on Malmquist's total factor productivity index. When TFP index =1, it means that the total factor productivity from t period to period t+1 does not change; When the TFP index > 1, it means that the TFP from t period to t+1 period has a positive growth; When the TFP index < 1, it means that the total factor productivity growth from t to t+1 is negative.

3.3. Source of data

The sample of this study was selected from the companies in the steel concept stock of Flush Finance listed on the Shanghai Stock Exchange before December 31, 2023. The companies with incomplete required data and large fluctuations in operating performance were excluded, and 35 listed steel companies were finally selected as the research objects. The sample time series was from 2018 to 2022, and the original financial index data came from the CSMAR database.

3.4. Dimensionless processing

Data standardization aims to eliminate incomparability between different indicators caused by dimensional differences. We used DEAP2.1 software to process data and carried out normalization of the original data, the specific calculation process is as follows:

$$X'_{ij} = \frac{X_{ij} - min(X_j)}{max(X_j) - min(X_j)} + 0.1 \quad (5)$$

X'_{ij} represents indicator j of company i, $\max(X_j)$ represents the maximum of indicator j, $\min(X_j)$ represents the minimum of indicator j.

3.5. Indicator Selection

The superiority of the DEA method is mainly reflected in the comprehensive evaluation of multi-input and multi-output. It requires the selected input and output indicators can effectively reflect the competitiveness level of DMUs and there is no obvious linear relationship between the indicators from the technical point of view. Finally considering the unity, comparability and availability of data. The selected indicators in this paper are shown in Table 1:

Table 1. Input Indicators and Output Indicators Selected

Categories	Indicators
Input indicators	Cost of sales [13]
	Research and Development expenditure [14]
	Total assets [15]
	Digital transformation word frequency
Output indicators	Total revenue
	Gross profit [13]
	Earnings per share

4. Empirical results

4.1. Static efficiency analysis

4.1.1. The geographical perspective of enterprises

Table 2. Data of Four economic regions using DEA

Year	Eastern			Central		
	Crste	Vrste	Scale	Crste	Vrste	Scale
2018	0.676	0.911	0.742	0.91	0.995	0.915
2019	0.89	0.963	0.925	0.971	0.979	0.992
2020	0.938	0.974	0.963	0.967	0.979	0.987
2021	0.883	0.924	0.956	0.96	0.983	0.977
2022	0.923	0.939	0.982	0.954	0.97	0.982
Mean	0.862	0.942	0.914	0.952	0.981	0.971
Year	Western			Northeast		
	Crste	Vrste	Scale	Crste	Vrste	Scale
2018	0.768	0.885	0.870	0.901	1.000	0.901
2019	0.917	0.959	0.956	0.928	1.000	0.928
2020	0.913	0.940	0.971	0.974	1.000	0.974
2021	0.901	0.972	0.929	0.957	1.000	0.957
2022	0.884	0.935	0.947	0.957	1.000	0.957
Mean	0.877	0.938	0.935	0.943	1.000	0.943

From the perspective of comprehensive technical efficiency, the comprehensive technical level of China's four major regions presents the characteristics of "Central > Northeast > Western > Eastern" (as shown in Table 2). Furthermore, the comprehensive technical efficiency of the four types is at a high level. From the perspective of pure technical efficiency and scale efficiency, the pure technical efficiency of enterprises in the northeast region is the largest, and the scale technical efficiency of enterprises in the central region is the largest. It shows that the enterprises in the northeast have done better in improving the technical level and optimizing the efficiency of the production process. The enterprises in the western region have taken appropriate measures in improving production capacity and optimizing resource allocation.

On the whole, the pure technical efficiency of these four types of enterprises is slightly greater than the scale efficiency, indicating that enterprises pay more attention to the introduction of high-tech talents and improve research and development capabilities in the development process, but enterprises need to balance the ratio of scale and input-output to achieve the highest resource utilization rate.

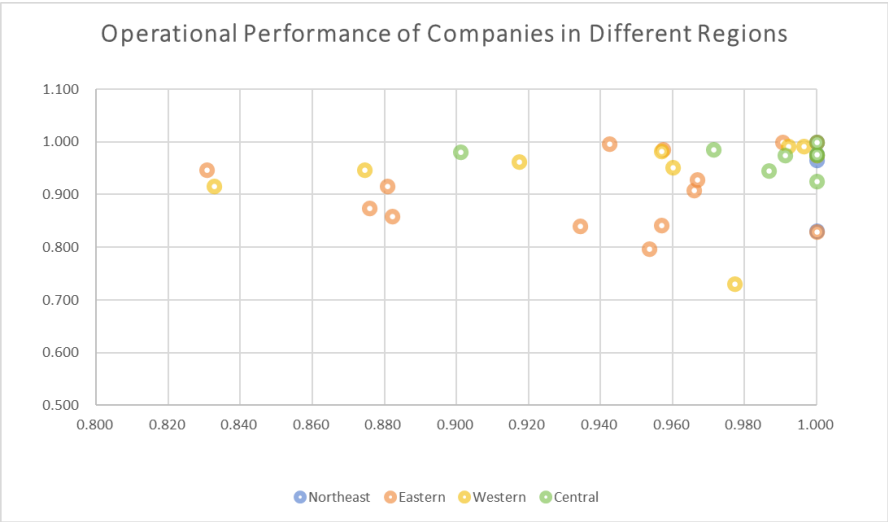


Figure 1. Scatter Diagram of Companies in Four Regions

Construct a scatter diagram with pure technical efficiency as X axis and scale efficiency as Y axis, and divide "double high", "high", "low high" and "double low" four types of areas by 0.94 and 0.9 respectively as shown in Figure 1.

- Double high type: the central region includes 7 enterprises, accounting for 87.50% of the total number of enterprises in the central region; The eastern region includes 7 enterprises, accounting for 46.67% of the total number of enterprises in the eastern region; The western region included four enterprises, accounting for 50.00% of the total; And the northeast region included three enterprises, accounting for 75.00 percent of the total. By contrast, the comprehensive technology level of enterprises in the western region and the eastern region is not high, and there is still a certain gap from the frontier. Therefore, enterprises in these two regions should not only improve the utilization efficiency of existing technology, equipment and human resources in the production process, but also maximize the production efficiency under a certain scale.
- High-low type: the eastern region includes 3 enterprises, accounting for 20.00% of the total number of enterprises in the eastern region; The western region includes 1 enterprise, accounting for 12.50% of the total number of enterprises in the western region; There is no central low region and northeast region. On the whole, the proportion of enterprises in these four regions is low, indicating that the steel industry in most regions pays attention to improving the technical level and the quality of employees in the development process to reduce waste in production and improve pure technical efficiency.
- Low-high type: the eastern region includes 2 enterprises, accounting for 13.33% of the total number of enterprises in the eastern region; The central region includes 1 enterprise, accounting for 12.50% of the total enterprises in the eastern region; The western region included three enterprises, accounting for 37.50 percent of the total enterprises in the western region; There is no northeast region. The proportion of enterprises in the western region is relatively high, so enterprises in the western region should focus on expanding production scale, improving production capacity, realizing economies of scale and improving scale efficiency in the development process.
- Double low type: the eastern region includes 3 enterprises, accounting for 20.00% of the total number of enterprises in the eastern region; No central region, western region and northeast region. In this type, only the eastern region has a certain proportion of enterprises in the four different regions. In the process of development, enterprises of this type should not only pay attention to expanding production scale and improving production capacity, but also improve technical level and staff quality to improve pure technical efficiency.

4.1.2. Enterprise ownership perspective

Table 3. Data of Companies of Two Ownership using DEA

Year	Government ownership			Private ownership		
	Crste	Vrste	Scale	Crste	Vrste	Scale
2018	0.801	0.95	0.842	0.628	0.843	0.746
2019	0.924	0.976	0.946	0.889	0.935	0.954
2020	0.943	0.969	0.973	0.944	0.981	0.963
2021	0.915	0.957	0.956	0.904	0.956	0.946
2022	0.922	0.952	0.968	0.942	0.954	0.987
Mean	0.901	0.9608	0.937	0.8614	0.9338	0.9192

As can be seen from Table 3, the average comprehensive technical efficiency of state-owned enterprises in the iron and steel industry is 0.901, and that of non-state-owned enterprises in intelligent manufacturing is 0.861. The comprehensive efficiency value of state-owned enterprises in the iron and steel industry is higher than that of non-state-owned enterprises. From the perspective of pure technical efficiency and scale efficiency, state-owned enterprises are higher than non-state-owned enterprises in both aspects. It shows that state-owned enterprises are stronger than non-state-owned enterprises in the optimization of production process efficiency and production capacity. On the whole, the pure technical efficiency of these two types of enterprises is higher, and they pay attention

to the utilization efficiency of existing technology, equipment and human resources in the process of development.

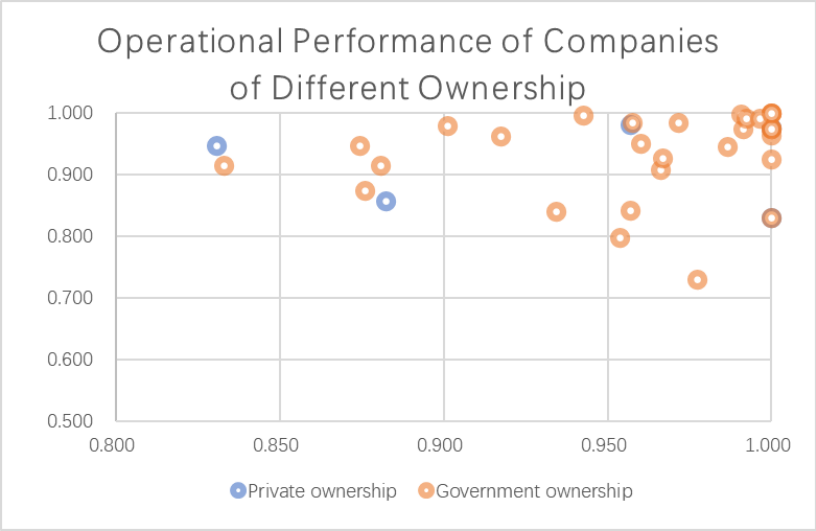


Figure 2. Scatter Diagram of Companies of Two Different Ownership

Construct a scatter diagram with pure technical efficiency as X axis and scale efficiency as Y axis, and divide "double high", "high", "low high" and "double low" four types of areas by 0.94 and 0.9 respectively as shown in Figure 2.

- Double-high type: State ownership includes 19 enterprises, accounting for 63.33% of the total number of state-owned enterprises; non-state ownership includes two enterprises, accounting for 40 percent of the total number of non-state enterprises. By contrast, the proportion of state-owned enterprises is greater than that of non-state-owned enterprises, so non-state-owned enterprises should pay attention to the further improvement of comprehensive technical efficiency.
- High-low type: State ownership includes 4 enterprises, accounting for 13.33% of the total number of state-owned enterprises; non-state ownership includes 1 enterprise, accounting for 20% of the total number of non-state enterprises. It can be seen from the proportion that there are more enterprises with high pure technical efficiency but low scale efficiency in non-state ownership. Such enterprises should focus on improving production capacity and optimizing resource allocation.
- Low-high type: State ownership includes 5 enterprises, accounting for 16.67% of the total number of state-owned enterprises; non-state ownership includes 1 enterprise, accounting for 20% of the total number of non-state ownership enterprises. The proportion of state-owned enterprises and non-state-owned enterprises is not much different, and both need to pay attention to improving research and development capabilities in the development process, introduce new products and new processes, and improve pure technical efficiency.
- Double low type: State ownership includes 2 enterprises, accounting for 6.67%of the total number of state-owned enterprises; non-state ownership includes 1 enterprise, accounting for 20% of the total number of non-state ownership enterprises. In this type of non-state ownership enterprises account for a relatively high proportion, so in the process of development, we should pay attention to improving production capacity, optimizing resource allocation, and improving research and development capacity and production process efficiency.

4.2. Analysis of TFP factors

Table 4. Data of TFP factors

Year	Effch	Techch	Pech	Sech	Tfpch
2018-2019	1.172	0.753	1.037	1.131	0.883
2019-2020	1.011	0.936	0.998	1.014	0.947
2020-2021	0.965	1.093	0.985	0.98	1.055
2021-2022	1.012	0.907	0.997	1.015	0.918
Mean	1.038	0.914	1.004	1.033	0.948

As can be seen from Table 4, from 2018 to 2022, the average total factor productivity index of listed enterprises in iron and steel industry is 0.948, indicating that the operating performance of listed enterprises in China's steel industry decreased by 5.20% on average annually. On the whole, the total factor productivity showed a downward trend during 2018-2019 and 2019-2020. It rebounded in 2020-2021, and then slowly declined in 2021-2022.

Generally speaking, the change value of pure technical efficiency indicated a trend of decreasing first and then stabilizing with an average annual growth rate of 0.4%, and peaked in 2018-2019, indicating that intelligent manufacturing enterprises realized technological innovation or improvement during this period and made efficient use of existing technologies and resources. At the same time, the change value of pure technical efficiency is consistent with the change value of comprehensive technical efficiency and scale efficiency, indicating that the improvement of pure technical efficiency of iron and steel enterprises and the control of enterprise scale have a greater impact on the operating efficiency of intelligent manufacturing enterprises. The average value of technological progress index is 0.914, which is the lowest in 2018-2019, indicating that enterprises lack of social and technological innovation in this year, leading to the regression of enterprise technical efficiency. On the whole, although the business performance of enterprises in technology and scale efficiency is slightly different from that of the base period, it remains at a high level.

5. Conclusion and Recommendations

Based on DEA and Malmquist index methods, this study measured the total factor productivity index of China's iron and steel industry from 2018 to 2022 and conducted static and dynamic analysis and comparison. The results show that: From the perspective of static analysis, the comprehensive technical level of the four regions in China presents the characteristics of "central > Northeast > Western> Eastern", and the comprehensive technical efficiency of the four types is at a high level. However, the pure technical efficiency of each region is slightly greater than the scale efficiency, indicating that enterprises need to balance the ratio of scale and input-output to achieve the highest resource utilization rate. The average comprehensive technical efficiency of state-owned enterprises is 0.901, and that of non-state-owned enterprises in intelligent manufacturing is 0.861. The comprehensive efficiency value of state-owned enterprises in the iron and steel industry is higher than that of non-state-owned enterprises. From the perspective of pure technical efficiency and scale efficiency, state-owned enterprises are higher than non-state-owned enterprises in these two aspects. It shows that state-owned enterprises are stronger than non-state-owned enterprises in the optimization of production process efficiency and production capacity. On the whole, the pure technical efficiency of these two types of enterprises is higher, and they pay attention to the utilization efficiency of existing technology, equipment and human resources in the process of development. Based on the above summary, this study presents the following recommendations:

Coordinate top-level design to drive digital transformation. In the context of digitalization, enterprises should strengthen system planning and top-level design, coordinate and promote the overall digital transformation of the group, and commit to building a digital platform that more effectively serves users at all levels. Based on the actual situation of enterprise digitalization, companies should fully consider the differences in informatization and formulate a blueprint structure.

Reinforce the incorporation of emerging information technology to enhance operational productivity within enterprises. Iron and steel companies ought to increase investment in research and development of new technologies, and implement "smart production, smart operation and smart service". Optimize the manufacturing process with new technologies, realize lean management of unit cost and flexible manufacturing of customer demand, and participate in market competition with competitive cost and high-quality products.

Focus on scale economy and technical efficiency coordination. Iron and steel industry ought to improve scale effect, reduce production costs, increase market share, and continue to optimize the structure. Enterprises should seek expansion methods to achieve the best economies of scale while maintaining flexibility to improve business performance.

Deepen and adhere to the strategy of coordinated regional development. Relevant state institutions should establish mechanisms for coordinating regional strategies and speed up the building of a new model of integrated and interactive development among different regions. It is crucial to improve the mechanism for integrated market development and promote the orderly and unrestricted movement of various production factors. Deepening regional cooperation mechanisms, strengthening collaboration within urban agglomerations, and fostering cooperation in border areas between provinces are essential. Enterprises within the four major economic regions should actively participate in collaborative efforts to boost trade flows and work towards a relatively balanced development.

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