Research on the Innovation Efficiency of Chinese Industrial IOT Companies Based on the Three-Stage DEA Method

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Abstract. The industrial internet of things has become the key foundation to support a new round of global industrial reform because of its deep integration of the new generation of information technology and industrial systems. Its own innovation efficiency is an important factor to determine the degree of industrial integration and the competitiveness of reform. Based on the data of Chinese industrial IOT companies and using the Three-stage DEA model, this paper calculates the innovation efficiency of Chinese industrial internet of things. The results show that most industrial IOT companies in China need to focus on the improvement of pure technical efficiency while increasing R&D investment. They should not only control the amount of investment, but also pay attention to the adjustment of input-output structure. According to the research results, this paper puts forward some countermeasures and suggestions to improve the innovation efficiency of industrial IOT companies.

Keywords: Industrial internet of things · Three-stage DEA model · Innovation efficiency evaluation

1 Introduction

The concept of Industrial Internet of Things was first put forward by General Electric in 2012, and it was promoted because of the establishment of Industrial Internet Alliance by five industry leading enterprises in the United States. Its meaning is a new business form based on the integration of internet of things technology and industry [9]. Its essence is to closely connect equipment, production lines, factories, suppliers, products and customers through an open global industrial network platform, so that enterprises can share various element resources in the industrial economy, reduce costs, improve efficiency and realize intelligent manufacturing.

Since 2017, China has released a number of policies and plans, such as the Guiding Opinions on Deepening the 'Internet + Advanced Manufacturing Industry' and Developing the Industrial Internet of Things, Action Plan on the Development of Industrial

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Internet of Things (2018–2020), Action Plan on innovative development of the industrial internet (2021–2023), so as to realize the integrated development of industrialization and informatization on a broader, deeper and higher level. A large number of industrial IOT companies have emerged. Industrial IOT companies are the economic entities that mainly participate in the development of IOT, including operators and communication equipment providers that provide industrial solutions with the help of channel advantages, internet giants that provide the support of the basic platform of industrial internet of things, IT companies that extend the original solutions to the industrial field, manufacturing companies that extend the original industrial equipment and instruments to automatic control and provide digital solutions, and high-tech companies that provide industrial software and internet of things services. These companies are highly active in the application realizability of industrial internet of things platform, technical capability of solutions, number of equipment connections, number of users, amount of data, industrial internet of things services, etc. Innovation, as the concentrated embodiment of the endogenous development power of industrial IOT companies, is the key to realize the deep integration of new generation information technology and industrial economy, and the key to a new round of industrial reform and competition. Therefore, it is particularly important to measure and evaluate the innovation efficiency of such companies. It has a great significance to realize intelligent manufacturing.

Data envelopment analysis (DEA) is a method to evaluate the efficiency of similar institutions with the goal of measuring 'relative efficiency' Keshava-rz [6]. The Three-stage DEA model improves the traditional single-stage DEA which ignores the impact of external environment and random error on efficiency, and integrates the advantages of stochastic frontier analysis (SFA), so that each decision-making unit is under the same environment and random factors, showing strong applicability in efficiency evaluation. Guo et al. [1] use Three-stage DEA to assess the efficiency of global intelligent innovation based on the data of R&D investment, e-government investment level, intelligence number of published papers, national high-tech exports, the government maturity level of artificial intelligence in 101 countries. Ribeiro et al. [8] focus on the Portuguese regional innovation systems and use the Three-stage DEA model to discuss the need of information disclosure on innovation level is provided to highlight the potential conflict between level and efficiency of innovation. Li et al. [7] measure the innovation efficiency of Chinese semiconductor industry based on generalized Three-stage DEA analysis. Huang et al. [3] use the Three-stage DEA model to calculate the innovation efficiency of emerging Gerontechonlogy industry and their subdivided industries from the two aspects of R&D process and achievement transformation process. Jia and Wang [4] evaluate and analyze the efficiency of scientific and technological innovation of industrial enterprises through Three-stage DEA model using the data of 31 provinces in China. Jia and Ding [5] discuss the impact of inter provincial cooperation network structure on enterprise innovation efficiency based on the Three-stage DEA model. However, at present, the research on industrial internet of things mostly focuses on the fields of development strategy, business model, technology application and security strategy, and the research on innovation efficiency is relatively lacking. A series of problems such as how to measure and evaluate the innovation efficiency of industrial IOT companies and what are the main factors restricting their development need to be further studied. Based on this,

this paper takes industrial IOT companies in China as the research objects, constructs innovation efficiency evaluation system, and measures them based on the three-stage DEA model.

2 Three-Stage DEA Model

This paper adopts the Three-stage DEA method proposed by Fried et al. (2002), which combines the non-parametric evaluation method DEA with the parametric evaluation method SFA.

In the first stage, we use raw input-output data for BCC model. For any DMU, the input-oriented BCC model can be expressed as:

$$\min \quad \theta - \varepsilon(e_m^T S^- + e_s^T S^+)$$
$$s.t. \begin{cases} \sum\limits_{j=1}^{n} X_j \lambda_j + S^- = \theta X_0 \\ \sum\limits_{j=1}^{n} Y_j \lambda_j - S^+ = Y_0 \\ \lambda_j \geq 0, \ S^-, S^+ \geq 0, \ j = 1, 2, \ldots, n \end{cases} \tag{1}$$

Among them, j represent decision units. X, Y are input and output vectors.θ is efficiency index of decision-making unit. λ is weight, $e_m^T = (1, 1, ..., 1)^T \in E^m$, $e_s^T = (1, 1, ..., 1)^T \in E^s$, s^- and s^+ are Input and output slack variables.

The second stage is based on SFA-like regression to remove environmental factors and statistical noise. The SFA-like regression function is constructed as:

$$S_{im} = f^i(Z_m, \beta^i) + \nu_{im} + \mu_{im}$$
$$i = 1, 2, \ldots, I, \ m = 1, 2, \ldots, M \tag{2}$$

S_{im} represents the mth input slack variable of the ith DMU. $f^i(Z_m, \beta^i)$ represents the effect of environmental variables. ϑ_{ik} represents a random error and μ_{ik} represents the management inefficiency.

According to the regression results, adjust the input of the decision-making unit, and the corresponding measurement equation is:

$$X_{im}^* = X_{im} + \left[\max_m\left\{z_m\hat{\beta}^i\right\} - z_m\hat{\beta}^i\right] + \left[\max_m\left\{\hat{\nu}_{im}\right\} - \hat{\nu}_{im}\right]$$
$$i = 1, 2, \ldots, I, \ m = 1, 2, \ldots, M \tag{3}$$

X_{im}^* is the adjusted input, X_{im} is the input before adjustment. $[\max_m\left\{Z_m\widehat{\beta^i}\right\} - Z_m\widehat{\beta^i}]$ represents the adjustment of all DMU to a homogeneous environment. $[\max_m\left\{\widehat{\vartheta_{im}}\right\} - \widehat{\vartheta_{im}}]$ represents the adjustment of the random error of all DMU to the same situation.

In the third stage, the adjusted input value is used to replace the traditional BCC model again.

3 Establishment of the Indicator System

3.1 Selection of Variables

Input variables should be selected according to the resources allocated for innovation, mainly including the R&D funds and R&D human capital resources. According to the previous studies, R&D funds are measured by R&D expenditures in the industrial IOT companies, and R&D human capital resources are measured by the number of developers.

The innovation output of industrial IOT companies should include two aspects: one is technical output and the other is economic output. The technical output is measured by the number of patent applications, and the economic output is measured by the main business income and total profit in the industrial IOT companies.

In recent years, the Chinese government has actively promoted the development of industrial internet of things, and has successively issued many policies and plans from the central government to the local government. The main supportive methods are government subsidies and financial support. Therefore, in order to identify the possible sources of innovation efficiency and differences among industrial IOT companies, these support policies should be used as environmental variables to reflect the effect of government guidance. At the same time, the development and innovation efficiency of industrial IOT companies are significantly affected by regions. Different regions can provide them with different material, human resources and different internet industry bases, therefore, basic socio-economic conditions need to be controlled. So all environmental variables include supportive policies and socioeconomic conditions. Supportive policies are divided into government subsidies and financial support, government subsidies are measured by the amount of government subsidies included in non recurring profits and losses, financial support is measured by the cash received from loans in the cash flow statement. Socioeconomic conditions include industrial foundation, computer density and talent support, industrial foundation is measured by the industrial added value of the region where the company is located, Computer density is measured by the number of computers per 100 people in the area where the company is located, and talent support is measured by the number of students in colleges and universities per 100000 population. The established indicator system is shown in Table 1.

3.2 Data Sources

Taking 2020 as the research time, combined with the industrial IOT concept stocks gave by Choice Financial Database and the description of the annual reports of public limited companies, this paper selects 55 public limited companies whose main businesses are highly related to industrial internet of things as the research samples, such as Shanghai Baosight Software Co., Ltd., Raisecom Technology CO., Ltd., Business-intelligence of Oriental Nations Corporation Ltd., Yonyou Network Technology Co., Ltd., Foxconn Industrial Internet Co., Ltd. and so on. These samples mainly cover the internet of things terminal and network connection, industrial software internet services, industrial internet of things platform, industrial information security and other industrial interconnection equipment, software or service supply companies.

Table 1. Evaluation indicator system of innovation efficiency of industrial IOT companies

Primary indicators	Secondary indicators	Tertiary Indicators
Innovation input	R&D funds	Total amount of R&D expenditures/Million yuan
	R&D human capital	The number of developers/Number of people
Innovation output	Technical output	Annual number of patents applied/Number
	Economic output	Main business income disclosed at the end of the period/Million yuan
	Total profit	Total profit disclosed at the end of the period/Million yuan
Innovation environm-ent	Government subsidy	Amount of government subsidies included in non recurring profits and losses/Million yuan
	Financial support	Cash received from borrowings in the enterprise cash flow statement/Million yuan
	Industrial foundation	Industrial added value in the region where the enterprise is located/Hundred million yuan
	Computer density	Number of computers per 100 people in the area where the enterprise is located/Number
	Talent support	Number of students in Colleges and universities per 100000 population in the area where the enterprise is located/Number of people

The financial data comes from the annual report of companies disclosed by Cninfo Website, the patent data comes from China and Global Patent Examination Information Inquiry, and other data comes from the National Bureau of statistics.

4 Results

4.1 Stage I: Analysis of BCC Model Calculation Results

In the first stage, based on the unadjusted input and output data, DEA-BCC model is used to calculate the innovation efficiency of 55 industrial IOT companies in 2020. The results are shown in Table 2.

From Stage I's results, on average, the industrial IOT companies innovation technical efficiency (TE) is 0.371, pure technical efficiency (PTE) is 0.499 and scale efficiency (SE) is 0.767. There are three companies that reached efficiency score equal to value 1. The waste of resources caused by technical efficiency is 62.9%, and the innovation efficiency needs to be improved.

Table 2. Average innovation efficiency and returns to scale of industrial IOT companies in the first stage

	Industrial IOT companies
TE on average	0.371
PTE on average	0.499
SE on average	0.767
Proportion of increasing returns to scale	49.09%
Proportion of constant returns to scale	7.27%
Proportion of diminishing returns to scale	43.64%

4.2 Stage II: SFA-Based Stochastic Frontier Analysis

Borrowing the results obtained in the Stage I to isolate the slack variables for each input variable [10]. The SFA analysis is used to obtain the influence of environmental factors on input slack, as shown in Table 3. In the regression results of the two input slack variables, LR test of the one-sided error both pass the significance test of 1%, indicating that it is necessary and reasonable to eliminate environmental factors and random interference. The regression coefficients of environmental variables mostly pass the significance test of 1%. It can be seen that supportive policies and socioeconomic conditions have a significant impact on the input redundancy of industrial IOT companies. According to the SFA regression results, analyze the impact of various environmental variables on the input indicators:

Government Subsidies. Table 3 shows regression coefficients for R&D expenditure's slack variable is significantly positive, for developer's slack variable is positive but it fails to pass the significance test. It shows that the increase of government subsidies is not conducive to the improvement of innovation efficiency of industrial IOT companies. The possible reason is that the increase of government subsidies improves the support for R&D may result a degree of redundancy and waste of resources in the existing management mode and output level, which reduces the innovation efficiency.

Financial Support. Financial support is a positive factor for the input target, because of the regression coefficients of the slack variables of the input index are negative. Especially for the raising of R&D funds, the use of financial support can effectively reduce the redundancy of investment and improve the innovation efficiency.

Industrial Foundation. Industrial foundation is a positive factor for the input target, because of the regression coefficients of the slack variables of the two input index are both significantly negative. It can be seen that the increase of industrial added value will create a good development environment, which is conducive to companies to reduce resource waste and R&D costs.

Table 3. SFA regression results

Dependent Variable	R&D expenditure Slack	Developer Slack
Constant	−120.861*** (−14.663)	−7.793*** (−2.034)
Government subsidy	67.584*** (3.983)	0.724 (0.269)
Financial support	−142.882*** (−32.975)	−7.628*** (−6.743)
Industrial foundation	−28.119*** (−2.804)	−3.357*** (−2.925)
Computer density	−64.790*** (−6.710)	−5.381*** (−4.763)
Talent support	56.308*** (7.528)	4.168*** (4.177)
σ^2	2.02E+05*** (2.02E+05)	9.30E+02*** (9.30E+02)
γ	0.999*** (83.080)	0.999*** (194.125)
LOGL	−374.862	−222.034
LR	30.679***	38.608***

***, **, * Significant at the 1%, 5%, 10% level, respectively; T value in parentheses.

Computer Density. Table 3 shows regression coefficients for R&D expenditure's slack variable and developers' slack variables are significantly negative. Computer density is the environmental basis for the development of industrial internet of things. The higher the density, the more conducive it is for enterprises to rely on the internet platform to realize manufacturing intelligence, network collaboration and digital management, so as to optimize resource allocation and improve innovation efficiency.

Talent Support. Table 3 shows regression coefficients for two inputs' slack variables are significantly positive, which reflect that in promoting innovation, companies have unreasonable talent arrangement and high labor cost, resulting in investment redundancy and affecting the improvement of R&D efficiency.

Due to the differences in the influence direction and intensity of each environmental variable on the input slack variable, in order to make the enterprise in the same comparative environment, adjust each input variable according to the SFA regression results, after excluding the influence of environmental factors and random factors, then explore the innovation efficiency under the same environmental conditions.

Table 4. Average innovation efficiency and returns to scale of industrial IOT companies in third stage

	Industrial IOT companies
TE on average	0.434
PTE on average	0.563
SE on average	0.738
Proportion of increasing returns to scale	78.18%
Proportion of constant returns to scale	12.73%
Proportion of diminishing returns to scale	9.09%

4.3 Stage III: Adjusted Innovation Efficiency Analysis

The adjusted input variables and original output variables are calculated by DEA-BCC model again to obtain the innovation efficiency value of industrial internet of things enterprises in the third stage. Then analyze innovation efficiency:

4.3.1 Analysis on Innovation Efficiency Value and Returns to Scale

Table 4 shows the average innovation efficiency and returns to scale of industrial IOT companies in the third stage. Comparing Table 2 and Table 4, it can be seen that after excluding the influence of environment and random factors, the average innovation comprehensive efficiency of industrial IOT companies increases from 0.371 to 0.434, and the average pure technical efficiency increases from 0.499 to 0.563, The average scale efficiency decreased from 0.767 to 0.738. The comprehensive efficiency of innovation has been improved, but there is still room for improvement, and the low pure technical efficiency is still the main reason restricting the rise of comprehensive efficiency of innovation.

From the perspective of returns to scale, after excluding the influence of environment and random factors in the third stage, the proportion of increasing returns to scale increased significantly, from 49.09% to 78.18%, and the proportion of decreasing returns to scale decreased significantly, from 43.64% to 9.09%. It can be seen that most industrial IOT companies are still in the stage of increasing returns to scale. Therefore, increasing the scale of innovation investment is conducive to increasing the innovation efficiency.

4.3.2 Analysis of Innovation Efficiency Types

Taking 0.7 as the critical point of pure technical efficiency and scale efficiency, 55 industrial internet of things enterprises are divided into five types. The distribution of the number of enterprises of each type is shown in Table 5.

Table 5. Distribution of companies with different innovation efficiency types

Type	Standard	Number of companies	Proportion
Innovation pioneer	PTE = 1	7	12.73%
	SE = 1		
Performs well	$0.7 \leq \text{PTE} < 1$	6	10.91%
	$0.7 \leq \text{SE} < 1$		
Scale efficiency improvement	$0.7 \leq \text{PTE} < 1$	3	5.45%
	$0 \leq \text{SE} < 0.7$		
Pure technical efficiency improvement	$0 \leq \text{PTE} < 0.7$	18	32.73%
	$0.7 \leq \text{SE} < 1$		
Innovation lagging	$0 \leq \text{PTE} < 0.7$	21	38.18%
	$0 \leq \text{SE} < 0.7$		

Innovation pioneer companies are the companies whose TE, PTE, and SE reach 1. After adjustment, there are 7 industrial IOT companies at the efficiency frontier. Compared with the results of the first stage, it is significantly increased. The pure technical efficiency and scale efficiency both are between 0.7–1, indicating that the innovation efficiency performs well. Scale efficiency improvement companies have higher pure technical efficiency, but lower scale efficiency. Such companies need to focus on improving scale efficiency. Pure technical efficiency improvement companies have higher scale efficiency, but lower pure technical efficiency. Such enterprises need to take the improvement of pure technical efficiency as the key. Companies with pure technical efficiency and scale efficiency less than 0.7 are classified as innovation lagging type. This kind of companies are mainly due to the sharp decline in scale efficiency after excluding the influence of environment and random factors, which is consistent with the fact that most companies have just developed the industrial internet of things.

4.3.3 Analysis on the Causes of Differences in Innovation Efficiency

According to the results of the third stage DEA model, the average innovation input redundancy and output deficiency of industrial internet of things enterprises are summarized, as shown in Table 6.

It can be seen from Table 6 that the radial movement of insufficient output of patent applications, main business income and total profit is 0 units, and there is insufficient output only in slack movement, indicating that remain the existing input structure the innovation efficiency can be improved directly by improving the slack movement of output. Especially for the economic output brought by industrial interconnection innovation, enterprises should further expand the market and increase their innovative business performance.

The average radial movement redundancy of R & D funds of industrial IOT companies is 213.561 units. It can be seen that there is serious blindness in R&D investment, and the input-output structure of innovation is unreasonable, which leads to low pure

Table 6. Redundant input and insufficient output of innovation in industrial IOT companies

Redundant input or insufficient output	Radial	Slack
Insufficient average number of patent applications/Number	0.000	2.006
Insufficient average main business income/Million yuan	0.000	3316.364
Insufficient total average profit/Million yuan	0.000	15.329
Average R&D expenditure redundancy/Million yuan	213.561	0.000
Average developer redundancy/Hundred people	11.041	1.967

technical efficiency. There are both radial movement redundancy and slack movement redundancy in R&D personnel investment, which are 1104.1 and 196.7 units respectively. It can be seen that there are both high cost of labour and unreasonable allocation of human resources in R&D personnel investment.

5 Conclusions

This paper uses the Three-stage DEA model to study the innovation efficiency of 55 industrial IOT companies. At present, the innovation efficiency of Chinese industrial IOT companies needs to be improved, and the low pure technical efficiency is the main reason restricting the rise of comprehensive innovation efficiency. After excluding the influence of environment and random factors, most non DEA effective industrial IOT companies are in the state of increasing returns to scale, a large number of them are facing the dual pressure of low pure technical efficiency and low scale efficiency at the same time. In terms of environmental variables, financial support, industrial foundation and computer density are conducive to improve the innovation efficiency of industrial IOT companies, while government subsidies and talent support lead to increased input redundancy. From the perspective of the reasons for the efficiency difference, the output mainly shows the insufficient slack movement, while the input has both excessive input and unreasonable structure.

Based on this, the following suggestions are put forward to improve the innovation efficiency of industrial IOT companies: (1) As a whole, the R&D investment scale of industrial IOT companies can be moderately expanded, and at this time, special attention should be paid to pure technical efficiency. As a new business form, industrial IOT companies should constantly reform system and promote the management of R&D investment, support the incubation of new innovative products, optimize the innovation input-output structure and reduce input redundancy. (2) Further consolidate the development foundation of industrial IOT, improve support policies, especially government subsidy policies, reasonably control the amount of subsidies, and make more use of market-oriented subsidies to support the improvement of innovation efficiency. Colleges and universities should further strengthen the training of information technology talents, so as to reserve professional application-oriented talents for the development of industrial internet of things.

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