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Efficiency Evaluation of China's Provincial Digital Economy Based on a DEA Cross-Efficiency Model

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Abstract: The Chinese government clearly put forward a strategy to speed up the development of the digital economy in “the 14th Five-Year” Plan, which will become the booster of China’s development. China has a vast territory and the state of development of the digital economy varies greatly across different regions. It is crucial to clarify the reasons for these differences and take measures to narrow them. Therefore, the evaluation and analysis of the current situation are conducive to the further development of the digital economy. Taking 30 provinces (excluding Tibet, Hong Kong, Macao and Taiwan) of China as the research objects, this paper constructs an index system taking digital infrastructure, digital technology and digital talent as input variables and taking digital industrialization and industrial digitization as output variables. The data envelopment analysis (DEA) cross-efficiency model is constructed to calculate and compare the cross-efficiency of the digital economies in each province. The results show the following: (1) The development efficiency of China’s digital economy has generally been low, and there is a large “digital divide” between provinces. (2) The input of digital talents is crucial for the digital economy in order to achieve high output and high efficiency, and high output is often accompanied by high efficiency. Based on the above conclusions, this paper puts forward some suggestions to promote the development of China’s digital economy.



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1. Introduction

With the in-depth development of the scientific and technological revolution and industrial transformation, the digital economy has become the core driving force in promoting the development of the global economy. The Chinese government has attached great importance to the new development opportunities led by the “digital economy”, serving to create new advantages of the digital economy and to promote digital industrialization and industrial digital transformation. Since the implementation of the digital economy development strategy in China, the scale of the digital economy has continued to grow, which has not only encouraged some business to undergo digital transformation but has also caused some traditional business to die out. The report of the “*National Digital Economy Development Index (2021)*” shows that China’s digital economy has continued to steadily improve; the national digital economy development index was 130.9 with a month-on-month growth of 2.4% and year-on-year growth of 15.3% as of December 2021. Meanwhile, it is expected that the scale of China’s digital economy will exceed CNY 60 trillion and the added value of the core industries of the digital economy will account for 10% of the Gross Domestic Product (GDP) by 2025. At present, the development of China’s digital economy is generally positive, but there are still some deficiencies. Due to different strategic

orientations, economic foundations, industrial structure and resource endowments, etc., the digital economy development of China's provinces shows obvious differences, which restricts the domestic and foreign dual circulation system to a certain extent. Therefore, it is very important to have a deep understanding of the development status of the digital economy in each province and take corresponding measures to promote its development.

Since the concept of the digital economy was proposed in the 1990s [1], some scholars have studied it. At present, the relevant theoretical research on the digital economy is mainly focused on the following three aspects: (1) The impact of digital economic development, which mainly includes national economic development [2], urban economic agglomeration [3], the high-quality development of the manufacturing industry [4–6], the industrial and employment structure [7–9], entrepreneurial activity [10], innovation efficiency [11], carbon emissions [12–15], green total factor productivity (GTFP) [16–19] and international comparisons of the development of digital economies [20]; (2) the driving factors of digital economy, which mainly include technology-driven [21] and innovation-driven factors [22], the foreign investment level, human capital, economic extroversion [23], the regional economic growth level [24] and domestic political and economic circumstances [25]; and (3) the spatial characteristics of digital economy. In China, there are many studies on the spatial differences of digital economy among different regions, which are manifested as the large gap in the development level of digital economy among regions. Moreover, empirical analysis shows that the unbalanced development of the digital economy in the Beijing–Tianjin–Hebei region of China is a serious problem [26]: the digital economy is mainly concentrated in the coastal areas and the middle reaches of the Yangtze and Yellow Rivers [27]; the spatial distribution of the digital economy is greater in eastern provinces such as Beijing, Shanghai, Guangdong, Jiangsu and Zhejiang, while it is lower in the central and western provinces [28]; the western region urgently needs to promote the construction of a digital economy and introduce high-tech digital economy talents [29]; the development level of the digital economy in the southern region is higher than that in the northern region [30]; and the degree of coupling coordination between the digital economy and high-quality development is higher in South, North and East China but lower in Central and Southwest China [31].

Data envelopment analysis (DEA) is a method proposed by Charnes, Cooper and Rhodes in 1978 to evaluate the relative effectiveness of Decision-Making Units (DMU). The traditional DEA model includes the Charnes–Cooper–Rhodes (CCR) model based on constant return to scale [32] and the Banker–Charnes–Cooper (BCC) model based on variable returns to scale [33]. However, it has many disadvantages [34]; for example, it can only distinguish whether the DMU is DEA-effective but does not sort the DMU, and it is easy to exaggerate its efficiency through self-evaluation alone. To solve these problems, various improved DEA models, such as the super-efficiency model [35], cross-efficiency model [36], benchmark ranking method [37], statistical methods for ranking such as canonical correlation analysis [38] and discriminant analysis [39], variable-weight DEA efficiency evaluation model [40], etc., have been proposed. The DEA cross-efficiency model has the following advantages: (1) It combines the efficiency of self-evaluation and other evaluations, avoiding the problem of unrealistic weight coefficients, and (2) the optimal DMUs can be comprehensively evaluated. Therefore, the cross-efficiency method has a wide range of applications in performance evaluation and ranking [41–46].

It can be noted that scholars have achieved certain results in research on the development of digital economies; however, there is still space for further expansion in research on the efficiency evaluation of provincial digital economic development. Firstly, the existing studies have mainly discussed the impact of the digital economy on the high-quality development of the manufacturing industry, carbon emissions and GTFP, etc., and paid insufficient attention to the overall development of the digital economy in China's provinces. Secondly, the existing studies usually divide spatial differences in the digital economy from the perspective of large regions and lack comparisons of the developmental efficiency of the digital economy from the perspective of the provinces. Comparison between provinces

is more suitable for these symptoms and can improve the overall level of China’s digital economic development. Meanwhile, the development of China’s digital economy is still in its early stages. In addition, China has a vast territory, and the developmental status of the digital economy varies greatly across different regions. It is crucial to clarify the reasons for these differences and take measures to narrow them. Therefore, based on the input–output efficiency evaluation index system of China’s digital economy, this paper uses the DEA cross-efficiency model to measure the developmental efficiency of China’s provincial digital economy and analyzes the existing problems regarding inter-provincial digital economy developmental efficiency as well as their causes by decomposing the efficiency index. We then put forward constructive suggestions in order to better promote the coordinated and stable development of China’s provincial digital economy.

2. DEA Model Establishment

2.1. The CCR Model

The CCR model (1978) is used to evaluate the relative effectiveness of the DMU with multiple inputs and multiple outputs, and its scale return is constant.

Suppose that there are n DMUs, where m and k represent the number of input indicators and output indicators, respectively, and x_j and y_j represent input indicator set and output indicator set of the j -th DMU. The matrix form is shown in Formula (1):

$$x_j = (x_{1j}, x_{2j}, \dots, x_{mj})^T \text{ and } y_j = (y_{1j}, y_{2j}, \dots, y_{kj})^T \tag{1}$$

The CCR model is shown in Formula (2):

$$h_0 = \max \frac{u^T y_0}{v^T x_0},$$

$$\text{s.t.} \begin{cases} \frac{u^T y_j}{v^T x_j} \leq 1 \\ u \geq 0, v \geq 0; j = 1, 2, \dots, n \end{cases} \tag{2}$$

where v_i and u_r are the weight coefficients of the i -th input index and the r -th output index, respectively, and $v = (v_1, v_2, \dots, v_m)^T, u = (u_1, u_2, \dots, u_k)^T$; here, x_0 and y_0 represent the input indicator set and output indicator set of the DMU being evaluated.

Charnes–Cooper transformation (1962) is performed using Formula (2), and the result is shown in Formula (3):

$$t = \frac{1}{v^T x_j}, \omega = tv, \mu = tu \tag{3}$$

Thus, the equivalent linear programming model is shown in Formula (4):

$$h_0 = \max \mu^T y_0,$$

$$\text{s.t.} \begin{cases} \omega^T x_j - \mu^T y_j \geq 0 \\ \omega^T x_j = 1 \\ \omega \geq 0, \mu \geq 0; j = 1, 2, \dots, n \end{cases} \tag{4}$$

Its dual model is shown in Formula (5):

$$\min \theta,$$

$$\text{s.t.} \begin{cases} \sum_{j=1}^n \lambda_j x_j \leq \theta x_0 \\ \sum_{j=1}^n \lambda_j y_j \geq y_0 \\ \lambda_j \geq 0; j = 1, 2, \dots, n \end{cases} \tag{5}$$

Introducing slack variables s^- and residual variables s^+ into Formula (5), it is converted to the following Formula (6):

$$\begin{aligned} & \min \theta, \\ & \text{s.t.} \begin{cases} \sum_{j=1}^n \lambda_j x_j + s^- = \theta x_0 \\ \sum_{j=1}^n \lambda_j y_j - s^+ = y_0 \\ \lambda_j \geq 0; j = 1, 2, \dots, n \\ s^- \geq 0, s^+ \geq 0 \end{cases} \end{aligned} \tag{6}$$

where θ is the efficiency value of the DMU; λ_j is the weight coefficient of the j -th DMU.

The following conclusions can be drawn based on the results of the model:

- (1) When $\theta = 1$ and $s^- = 0, s^+ = 0$, the j -th DMU is DEA-effective;
- (2) When $\theta = 1$ and $s^- > 0$ or $s^+ > 0$, the j -th DMU is weakly DEA-effective;
- (3) When $\theta < 1$, the j -th DMU is non-DEA-effective.

2.2. The DEA Cross-Efficiency Model

The DMUs of the CCR model are evaluated through the method of self-evaluation, while the DEA cross-efficiency evaluation method can eliminate this defect, and the cross-efficiency value is determined through its self-evaluation and other evaluations.

For the d -th evaluated object DMU_d , its efficiency value E_d in the CCR model can be solved through linear programming, as shown in Formula (7):

$$\begin{aligned} E_d &= \max \sum_{r=1}^k \mu_{rd} y_{rd}, \\ & \text{s.t.} \begin{cases} \sum_{i=1}^m \omega_{id} x_{id} = 1 \\ \sum_{r=1}^k \mu_{rd} y_{rj} - \sum_{i=1}^m \omega_{id} x_{ij} \leq 0 \\ \omega_{id} \geq 0, \mu_{rd} \geq 0; j = 1, 2, \dots, n \\ i = 1, 2, \dots, m; r = 1, 2, \dots, k \end{cases} \end{aligned} \tag{7}$$

where E_d is the self-evaluation efficiency; x_{ij} represents the value of the i -th input indicator of the j -th DMU, $x_{ij} > 0$; y_{rj} and y_{rd} represent the values of the r -th output index of the j -th DMUs and d -th DMUs, respectively, $y_{rj} > 0, y_{rd} > 0$; and ω_{rd} and μ_{id} represent the corresponding input and output index weight coefficients, respectively.

Let the optimal solution of the DMU_d s and DMU_j s based on Formula (7) be $(\omega_{id}^*, \mu_{rd}^*)$ and $(\omega_{ij}^*, \mu_{rj}^*)$. Then, the cross-efficiency of the DMU_j relative to the optimal weight coefficient of DMU_d can be defined as shown in Formula (8):

$$E_{dj} = \frac{\sum_{r=1}^k \mu_{rd}^* y_{rj}}{\sum_{i=1}^m \omega_{id}^* x_{ij}}; d = 1, 2, \dots, n; j = 1, 2, \dots, n. \tag{8}$$

where E_{dj} is the other-evaluation efficiency of the j -th DMU relative to the d -th DMU, the cross-efficiency matrix is $(E_{dj})_{n \times n}$, and $\bar{E}_j = \frac{1}{n} \sum_{d=1}^n E_{dj}$ represents the average value of its self-evaluation and other-evaluation efficiency, that is, the cross-efficiency value.

3. Empirical Analysis

3.1. Indicator Selection

The “China Digital Economy Development Index Report (2022)” highlights that the indicators affecting China’s digital economic development index mainly include digital industrialization, industrial digitization, digital infrastructure, digital technology and digital talent. Therefore, this paper uses these five indicators as the input–output indicators of China’s digital economic development efficiency. According to the meanings of the indicators, digital infrastructure, digital technology and digital talent are selected as the

input indicators, while digital industrialization and industrial digitization are selected as the output indicators. At the same time, in view of previous research [8,47–50] and the principles of data availability, strong discrimination and accuracy, the indicator system is quantified as shown in Table 1.

Table 1. The efficiency evaluation index system.

Indicator Type	Indicator Type	Indicator Representative
Input indicator	Digital infrastructure (Input 1)	Number of internet broadband access ports ($\times 10^4$)
	Digital technology (Input 2)	Fixed assets in information transmission, software and information technology services ($\times \text{CNY } 10^8$)
	Digital talent (Input 3)	Employed persons in information transmission, software and information technology services ($\times 10^4$ persons)
Output indicator	Digital industrialization (Output 1)	Software business revenue ($\times \text{CNY } 10^8$)
	Industrial digitalization (Output 2)	E-commerce sales ($\times \text{CNY } 10^8$)

3.2. Data Sources

The data sources of this paper are from the “China Statistical Yearbook”. In addition, since some data from Tibet have not been released, Tibet is excluded. While Hong Kong, Macao and Taiwan are not considered, the remaining 30 provinces are taken as research objects to calculate the input–output efficiency of China’s digital economy in 2020.

3.3. Input–Output Efficiency of China’s Provincial Digital Economy in 2020

The data of each province for 2020 were selected to evaluate the digital economy efficiency of each province using the DEA cross-efficiency model. The evaluation results are shown in Table 2.

As can be seen from Table 2, the average \bar{E}_j of the 30 provinces in China for 2020 is 0.4223, indicating that the overall efficiency of the provincial digital economy was low in China, that is, the overall utilization level of China’s digital economy was low under the given provincial resource input. Among the provinces, Chongqing ranks first, with an efficiency value of 0.9768, while Heilongjiang has the lowest efficiency value of 0.0679, indicating that there is a large “digital divide” between provinces.

The three input variables and cross-efficiency values of the 30 provinces were sorted in the order of smallest to largest, and the median of the serial number is 15.5. Then, the difference between the ranking of the cross-efficiency values of each province was determined, and 15.5 was taken as the vertical axis coordinate of each province. The difference between the ranking of the three input variables of each province was also determined, and 15.5 was taken as the horizontal axis coordinate of each province. We drew a location scatter plot of each province so as to determine the classification positioning of the input–output efficiency of the digital economy in each province.

In the positioning map, the provinces in the first quadrant are defined as the “input advantage-output stability type” of digital economy, for which the efficiency of the digital economy is also higher than the average level when a certain input variable is higher than the average level. This indicates that the province has made full use of the advantage of a certain input of the digital economy and translated it into the improvement of digital economic efficiency. The provinces in the second quadrant are defined as the “input disadvantage-output aggressive type” of digital economy, for which the efficiency of the digital economy is higher than the average level when a certain input variable is lower than the average level. This indicates that the province has overcome the disadvantage of a certain input, actively improved the efficiency of its digital economy and achieved good results. The provinces in the third quadrant are defined as the “input disadvantage-output conservative type” of digital economy, for which the efficiency of the digital economy is

also lower than the average level when a certain input variable is lower than the average level. This indicates that the province has not overcome the disadvantage of a certain input, and the efficiency of the digital economy is still not high. The provinces in the fourth quadrant are defined as the “input advantage-output potential type” of digital economy, for which the efficiency of the digital economy is lower than the average level when a certain input variable is higher than the average level. This indicates that the province has not made full use of the advantage of a certain input of the digital economy, and the efficiency of the digital economy still has great potential to improve.

Table 2. The evaluation results for the cross-efficiency of the digital economy in each province in 2020.

Rank	Province	\bar{E}_j
1	Chongqing	0.9768
2	Tianjin	0.8474
3	Shanghai	0.8363
4	Shandong	0.7614
5	Jiangsu	0.6763
6	Guangdong	0.6747
7	Zhejiang	0.6705
8	Beijing	0.6171
9	Fujian	0.5115
10	Anhui	0.4997
11	Liaoning	0.4884
12	Inner Mongolia	0.4309
13	Hubei	0.4127
14	Sichuan	0.3809
15	Hunan	0.3781
16	Jiangxi	0.3691
17	Shaanxi	0.3685
18	Shanxi	0.3479
19	Yunnan	0.3241
20	Hainan	0.3121
21	Guizhou	0.2787
22	Hebei	0.2727
23	Guangxi	0.2551
24	Ningxia	0.1910
25	Henan	0.1840
26	Qinghai	0.1453
27	Xinjiang	0.1337
28	Gansu	0.1309
29	Jilin	0.1259
30	Heilongjiang	0.0679
	Mean value	0.4223

By observing the output efficiency from the input perspective in Figure 1, it can be seen that the distributions of the provinces in terms of digital infrastructure and digital technology are similar.

Firstly, the typical provinces of the “input advantage-output stability type” are Shandong, Jiangsu and Guangdong. These provinces are located in the developed coastal areas, and their digital infrastructure and digital technology inputs are relatively well-developed and fully utilized, which is conducive to maintaining a high level of output efficiency. Secondly, the typical provinces of the “input disadvantage-output aggressive type” are Tianjin, Chongqing and Shanghai. These provinces are municipalities, and their overall investment level for digital infrastructure and digital technology is lower than the average due to their regional area and population. However, their per capita investment is not low, and they can make full use of input resources and achieve a higher-than-average efficiency level. Thirdly, the typical provinces of the “input disadvantage-output conservative type” include Ningxia, Qinghai and Gansu, which are located in Northwest China. The inputs of digital

infrastructure and digital technology are relatively scarce, and economic development is hindered. Meanwhile, the utilization of these provinces' resources is still not effective, which leads to their low output efficiency. Fourthly, the typical provinces of the "input advantage-output potential type" are Henan and Hebei, which are located in Central China, and their inputs of digital infrastructure and digital technology are higher than the average level. Their low efficiency is most likely caused by their poor input scale and structure, but their output efficiency still has great potential to improve.



Figure 1. (a) Input–output efficiency positioning of the digital economy in China’s provinces under the digital infrastructure input. (b) Input–output efficiency positioning of the digital economy in China’s provinces under the digital technology input.

Compared with digital infrastructure and digital technology, there are large differences in some provinces from the perspective of digital talents, as shown in Figure 2. For example, Beijing and Shanghai jump from the second quadrant or the middle level to the top of the first quadrant. Regarding Beijing, as the capital of China, and Shanghai, as the economic center of China, it is undoubted that their attraction of digital talents is the strongest, and they can also make full use of their talent advantages to achieve a high output efficiency.

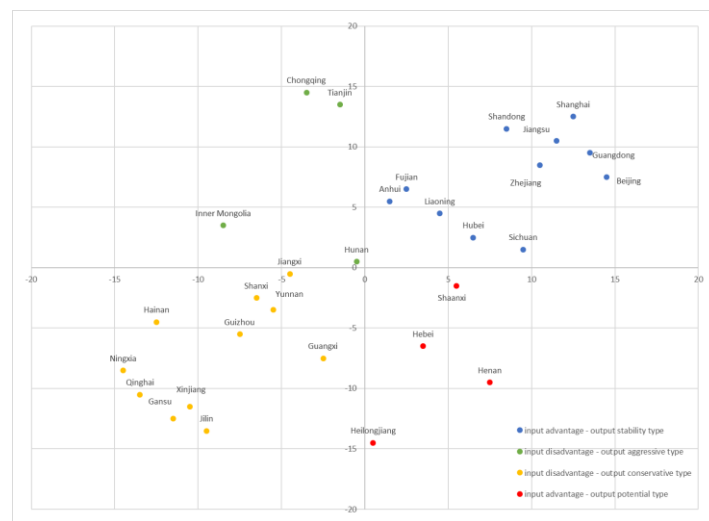


Figure 2. Input–output efficiency positioning of the digital economy in China’s provinces under the digital talent input.

In order to explore the influence of digital talent on digital economic efficiency, we added the output dimension, and the average values of the input, output and cross-

efficiency were taken as benchmarks to enable the results to reflect the effect of quantity. Then, we drew the table shown in Table 3. “High input” or “high output” is defined as an input or output above its average value, which denoted as “√” in the table.

Table 3. The cross-efficiency values and relative input–output of the digital economy in 30 provinces in 2020.

Rank	Province	Input 1	Input 2	Input 3	Total Output
1	Chongqing				
2	Tianjin				
3	Shanghai			√	√
4	Shandong	√	√	√	√
5	Jiangsu	√	√	√	√
6	Guangdong	√	√	√	√
7	Zhejiang	√	√	√	√
8	Beijing			√	√
9	Fujian	√	√		
10	Anhui	√			
11	Liaoning	√	√		
12	Inner Mongolia	√			
13	Hubei	√	√	√	√
14	Sichuan				
15	Hunan				
16	Jiangxi	√	√		
17	Shaanxi		√		
18	Shanxi				
19	Yunnan				
20	Hainan				
21	Guizhou				
22	Hebei	√	√		
23	Guangxi	√	√		
24	Ningxia				
25	Henan	√	√	√	
26	Qinghai				
27	Xinjiang		√		
28	Gansu				
29	Jilin				
30	Heilongjiang				

Note: The output indicators, “digital industry” and “industrial digitalization”, selected in this paper are both in units of CNY 100 million; thus, their sum is taken as the total output.

As can be seen from Table 3, the input level of digital talent is closely related to the output level. A high output is often accompanied by a high digital talent input. For example, Shanghai and Beijing have not invested much in digital infrastructure and digital technology, but their high digital talent inputs have yielded a high output and high efficiency. On the contrary, Fujian, Anhui, Hunan, Hebei and Guangxi all undertake high investment in digital infrastructure and digital technology, but their outputs are not high, which contradicts the importance of a high digital talent input for a high output. In terms of the low output of Hunan and Hebei Provinces, their digital talent inputs are only slightly higher than the average, probably due to the fact that the advantages of digital talent are not obvious, leading to the low output. In addition, there is a strong correlation between high output and high efficiency. The efficiency ranking of the high-output provinces shows that they are all above the average level, though there are also cities with low input and low output but high efficiency, such as Chongqing and Tianjin, as explained in the positioning analysis.

To sum up, high-output provinces generally have abundant digital talent resources and high efficiency ranking, indicating that investment in digital talent is the key to achieve high output and high efficiency, and high output is usually accompanied by high efficiency.

4. Conclusions and Suggestions

4.1. Conclusions

With digital infrastructure, digital technology and digital talent as input variables and digital industrialization and industrial digitalization as output variables, this paper constructed a DEA cross-efficiency evaluation model of China's provincial digital economy and analyzed the cross-efficiency evaluation results of provincial digital economies. The conclusions of this paper mainly include the following aspects: Firstly, the development efficiency of China's digital economy is generally low, and there is a large "digital divide" between provinces. Secondly, the input of digital talents is crucial for the digital economy, enabling it to achieve a high output and high efficiency, and a high output is often accompanied by high efficiency.

4.2. Suggestions

On the basis of the above research, combined with the current development status of the digital economy, this paper puts forward the following suggestions:

Firstly, we should accelerate the cultivation of digital talents as an "urgent need" and a "long-term solution". China's digital talent gap is close to 11 million, and with the rapid advancement of industry-wide digitalization, the demand gap for digital talents will continue to increase. Therefore, the government should speed up the adjustment of the talent training structure and increase the intensity of talent training, especially in provinces where digital talents are scarce, such as Guangxi, Hebei, Hunan and other provinces that already undertake high investment in infrastructure and technology. At the same time, these provinces should improve their talent incentive measures to retain talents for the digital economy.

Secondly, we should narrow the gap in digital economies between provinces, strengthen regional cooperation, break down digital barriers and promote smooth internal and external circulation. The provinces with highly developed, efficient digital economies such as Chongqing, Tianjin, Shanghai, Shandong and other provinces need to play a positive radiation and driving role to guide the coordinated development of the digital economy in Central China and make proper use of the advantages of the vast territory and rich new energy resources of Western China to help them to develop their digital economies. Central China not only connects the east to the west but also has the unique advantages of abundant resources, developed transportation and a good industrial foundation. For example, Henan, Hebei, Shanxi, Jiangxi and other provinces can use digitalization to empower traditional industries and develop modern service industries. Northwestern Chinese provinces such as Gansu, Xinjiang, Qinghai, Ningxia and Northeastern Chinese provinces such as Heilongjiang and Jilin should also improve their attractiveness in order to attract high-tech talents.

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References

1. Tapscot, D. *The Digital Economy: Promise and Peril in the Age of Networked Intelligence*; Educom Review; McGraw-Hill: New York, NY, USA, 1996.
2. Shim, J.-H. Analysis of the Influence of Digital Economy Development on the Korean Economy: Focusing on E-commerce. *J. Ind. Econ. Bus.* **2020**, *33*, 1591–1605. [[CrossRef](#)]
3. Xu, Z.; Gao, Y.; Huo, Z. Digital economic development of urban agglomeration economy effect. *Stat. Decis.* **2022**, *38*, 80–84. [[CrossRef](#)]
4. D'souza, C.; Williams, D. The Digital Economy. *Bank Can. Rev.* **2017**, *5*–18.
5. Hui, N.; Yang, X. Driving force of digital economy and the development of Chinese manufacturing high quality. *J. Shaanxi Norm. Univ. Philos. Soc. Sci. Ed.* **2022**, *51*, 133–147. [[CrossRef](#)]
6. Liu, X.X.; Hui, N. Study on the impact of digital economy on the high-quality development of China's manufacturing industry. *Reform Econ. Syst.* **2021**, *5*, 92–98.
7. Zhao, S.; Peng, D.; Wen, H.; Song, H. Does the Digital Economy Promote Upgrading the Industrial Structure of Chinese Cities? *Sustainability* **2022**, *14*, 10235. [[CrossRef](#)]
8. Si, X.F.; Li, M.S. Digital economy, employment structure and employment quality: An empirical analysis based on provincial data of China. *Northwest Popul. J.* **2022**, *43*, 54–69. [[CrossRef](#)]
9. Liu, Y.; Chen, X.D. Digital economy development of China's influence on the upgrading of industrial structure. *J. Econ. Manag. Res.* **2021**, *42*, 15–29. [[CrossRef](#)]
10. Zhao, T.; Zhang, Z.; Liang, S. Digital economy, entrepreneurial activity and high-quality development: Empirical evidence from Chinese cities. *Manag. World* **2020**, *36*, 65–76. [[CrossRef](#)]
11. Ding, C.; Liu, C.; Zheng, C.; Li, F. Digital Economy, Technological Innovation and High-Quality Economic Development: Based on Spatial Effect and Mediation Effect. *Sustainability* **2022**, *14*, 216. [[CrossRef](#)]
12. Hao, X.; Wen, S.; Li, Y.; Xu, Y.; Xue, Y. Can the digital economy development curb carbon emissions? Evidence from China. *Front. Psychol.* **2022**, *13*, 938918. [[CrossRef](#)]
13. Yu, H.; Zhu, Q. Impact and mechanism of digital economy on China's carbon emissions: From the perspective of spatial heterogeneity. *Environ. Sci. Pollut. Res.* **2022**, *30*, 9642–9657. [[CrossRef](#)] [[PubMed](#)]
14. Yi, M.; Liu, Y.; Sheng, M.S.; Wen, L. Effects of digital economy on carbon emission reduction: New evidence from China. *Energy Policy* **2022**, *171*, 113271. [[CrossRef](#)]
15. Zhang, W.; Liu, X.; Wang, D.; Zhou, J. Digital economy and carbon emission performance: Evidence at China's city level. *Energy Policy* **2022**, *165*, 112927. [[CrossRef](#)]
16. Meng, F.S.; Zhao, Y. How does digital economy affect green total factor productivity at the industry level in China: From a perspective of global value chain. *Environ. Sci. Pollut. Res.* **2022**, *29*, 79497–79515. [[CrossRef](#)]
17. Zhu, X.A.; Ma, Y.G. Study on the Impact of Digital Economy on the Change of Green Total Factor Productivity. *Econ. Probl.* **2022**, *11*, 1–11. [[CrossRef](#)]
18. Zhang, Y.H.; Wang, M.F.; Cui, L.M.; Kuang, A.P. Impact of the digital economy on green total factor productivity in Chinese cities. *J. Econ. Geogr.* **2022**, *42*, 33–42. [[CrossRef](#)]
19. Lyu, Y.; Wang, W.; Wu, Y.; Zhang, J. How does digital economy affect green total factor productivity? Evidence from China. *Sci. Total. Environ.* **2023**, *857*, 159428. [[CrossRef](#)]
20. Moroz, M. The level of development of the digital economy in Poland and selected European countries: A comparative analysis. *Found. Manag.* **2017**, *9*, 175–190. [[CrossRef](#)]
21. Li, Y.Z.; Ren, X.G. The Dynamic mechanism, operation path and Development Countermeasures of digital Economy Innovation from the perspective of Science and Technology. *Guizhou Soc. Sci.* **2020**, *12*, 113–120. [[CrossRef](#)]
22. Wang, S.P.; Teng, T.W.; Xia, Q.F.; Bao, H. The Spatial and temporal characteristics of the development level of China's digital economy and its innovation driving mechanism. *Econ. Geogr.* **2022**, *42*, 33–43. [[CrossRef](#)]
23. Nie, C.T.; Zhang, F. Regional differences and driving factors of the digital economy development level in China: An empirical analysis based on spatial panel model. *Tech. Econ. Manag. Res.* **2022**, *4*, 105–110.
24. Liu, J.; Yang, Y.Y.; Zhang, S.F. Measurement and Driving Factors of China's digital Economy. *Shanghai Econ. Res.* **2020**, *6*, 81–96. [[CrossRef](#)]
25. Arnold, S. Drivers and Barriers of Digital Market Integration in East Africa: A Case Study of Rwanda and Tanzania. *Politi. Gov.* **2022**, *10*, 106–115. [[CrossRef](#)]
26. Peng, W.B.; Han, D.C.; Yin, Y.; Yang, Y.; Shi, X.F.; Kuang, J.S. Spatial Effects of Digital Economy in Beijing-Tianjin-Hebei Region. *Econ. Geogr.* **2022**, *42*, 136–143+232. [[CrossRef](#)]
27. Li, Z.; Liu, Y. Research on the Spatial Distribution Pattern and Influencing Factors of Digital Economy Development in China. *IEEE Access* **2021**, *9*, 63094–63106. [[CrossRef](#)]
28. Luo, R.; Zhou, N. Dynamic Evolution, Spatial Differences, and Driving Factors of China's Provincial Digital Economy. *Sustainability* **2022**, *14*, 9376. [[CrossRef](#)]
29. Cheng, C.; Huang, H. Evaluation and Analysis of Regional Economic Growth Factors in Digital Economy Based on the Deep Neural Network. *Math. Probl. Eng.* **2022**, *2022*, 1121886. [[CrossRef](#)]

30. Tang, L.; Lu, B.; Tian, T. Spatial Correlation Network and Regional Differences for the Development of Digital Economy in China. *Entropy* **2021**, *23*, 1575. [[CrossRef](#)]
31. Han, Z.A.; Wu, H.Z.; Zhao, J.F. Research on Measurement and Evaluation of Coupling Coordination between Digital Economy and high-quality Development. *Stat. Inf. Forum* **2022**, *37*, 22–34.
32. Charnes, A.; Cooper, W.W.; Rhodes, E. Measuring the efficiency of decision making units. *Eur. J. Oper. Res.* **1978**, *2*, 429–444. [[CrossRef](#)]
33. Banker, R.D.; Charnes, A.; Cooper, W.W. Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. *Manag. Sci.* **1984**, *30*, 1078–1092. [[CrossRef](#)]
34. Liang, L.; Wu, J. A retrospective and perspective view on cross efficiency of data envelopment analysis (DEA). *J. Univ. Sci. Technol. China* **2013**, *43*, 941–947. [[CrossRef](#)]
35. Andersen, P.; Petersen, N.C. A Procedure for Ranking Efficient Units in Data Envelopment Analysis. *Manag. Sci.* **1993**, *39*, 1261–1264. [[CrossRef](#)]
36. Sexton, T.R.; Silkman, R.H.; Hogan, A.J. Data envelopment analysis: Critique and extensions. *New Dir. Program Eval.* **1986**, *1986*, 73–105. [[CrossRef](#)]
37. Charnes, A.; Clark, C.T.; Cooper, W.W.; Golany, B. A developmental study of data envelopment analysis in measuring the efficiency of maintenance units in the U.S. air forces. *Ann. Oper. Res.* **1985**, *2*, 95–112. [[CrossRef](#)]
38. Friedman, L.; Sinuany-Stern, Z. Scaling units via the canonical correlation analysis in the DEA context. *Eur. J. Oper. Res.* **1997**, *100*, 629–637. [[CrossRef](#)]
39. Sinuany-Stern, Z.; Mehrez, A.; Barboy, A. Academic departments efficiency via DEA. *Comput. Oper. Res.* **1994**, *21*, 543–556. [[CrossRef](#)]
40. Yang, F.; Liang, L.; Bi, G.B.; Zha, Y. DEA efficiency evaluation model based on diverse weights. *China J. Manag. Sci.* **2008**, *S1*, 84–87. [[CrossRef](#)]
41. Green, R.H.; Doyle, J.R.; Cook, J.R. Preference voting and project ranking using DEA and cross-evaluation. *Eur. J. Oper. Res.* **1996**, *90*, 461–472. [[CrossRef](#)]
42. Falagario, M.; Sciancalepore, F.; Costantino, N.; Pietroforte, R. Using a DEA-cross efficiency approach in public procurement tenders. *Eur. J. Oper. Res.* **2012**, *218*, 523–529. [[CrossRef](#)]
43. Chen, W.; Li, S.-S.; Zhang, J.; Mehlawat, M.K. A comprehensive model for fuzzy multi-objective portfolio selection based on DEA cross-efficiency model. *Soft Comput.* **2020**, *24*, 2515–2526. [[CrossRef](#)]
44. Chen, L.; Wu, F.; Wang, Y.; Li, M. Analysis of the environmental efficiency in China based on the DEA cross-efficiency approach under different policy objectives. *Expert Syst.* **2020**, *37*, e12461. [[CrossRef](#)]
45. Chen, L.; Wang, Y.M. DEA cross-efficiency target setting approach based on different decision-making context. *Syst. Eng.-Theory Pract.* **2021**, *41*, 2683–2695. [[CrossRef](#)]
46. Sun, Y.; Wang, K.Y.; Yao, X.D. Economic benefits evaluation of urban public infrastructure based on the DEA cross-efficiency method. *China Soft Sci. Mag.* **2015**, *1*, 172–183.
47. Wang, J.; Zhu, J.; Luo, X. Research on the measurement of China's digital economy development and the characteristics. *J. Quant. Technol. Econ.* **2021**, *38*, 26–42. [[CrossRef](#)]
48. Cheng, G.B.; Li, Y. Regional differences and efficiency evaluation of digital economy development level based on in-put-output perspective. *Stat. Decis.* **2022**, *38*, 109–113. [[CrossRef](#)]
49. Jin, C.Y.; Xu, A.T.; Qiu, K.Y. Measurement of China's provincial digital economy and its spatial correlation. *J. Stat. Inf.* **2022**, *6*, 11–21.
50. Fan, H.J.; Wu, T. Digitalization measure and index system construct in China. *J. Cap. Univ. Econ. Bus.* **2020**, *22*, 3–12. [[CrossRef](#)]

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