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Research On The Evaluation Of Intelligent Level Of Listed Manufacturing Enterprises

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Abstract:
This paper takes the listed manufacturing enterprises in China's A-share market from 2010 to 2021 as the research sample. By constructing A multi-dimensional index system, it systematically calculates and analyzes the intelligence level and total factor productivity of manufacturing enterprises. The study selected 9,840 sample data from 820 listed manufacturing enterprises, based on principles such as objectivity and data availability. A level of intelligence has been established, which includes six indicators: hardware foundation, software foundation, talent foundation, capital foundation, R&D intensity, and innovation ability. The evaluation system uses principal component analysis to calculate the intelligence index. Meanwhile, the DEA-Malmquist index method is adopted. With the net value of fixed assets and the total number of employees as input indicators, and the return on main business assets, operating income and net profit as output indicators, the total factor productivity of the enterprise is calculated.
The research finds that from a regional perspective, there are significant differences in the intelligence levels among provinces. Beijing (0.519), Hubei (0.187), and Guangdong (0.177) have the highest intelligence indices, while Gansu (-0.620), Qinghai (-0.625), and Ningxia (-0.825) have the lowest. By region, the eastern region (-0.342) > the central region (-0.408) > the northeastern region (-0.506) > the western region (-0.524), and the overall intelligence index increased from -1.087 to 0.355 from 2010 to 2021.
In terms of total factor productivity, all provinces showed positive growth. Yunnan (11.1%), Xinjiang (11%), and Tianjin (9.7%) had the fastest growth rates, while Anhui (5.4%), Hainan (4.8%), and Qinghai (2.5%) had the slowest growth rates. At the regional level, the western region (8%) > the northeastern region (7%) > the eastern region (6.9%) ≈ the central region (6.8%). Due to the high base, the marginal growth rate of high-tech industries is lower than that of traditional industries. This study provides methodological and empirical support for quantifying the intelligence level of the manufacturing industry and analyzing regional and industry differences, and offers data references for precisely promoting intelligent upgrades.
Keywords: *The intelligence level of listed manufacturing enterprises, total factor productivity, principal component analysis method, DEA-Malmquist index method*

1.INTRODUCTION

This article intends to extract the occurrence frequency of keywords related to intelligent hardware and intelligent software through data mining technology as an indicator reflecting the degree of intelligence. Combined with other traditional indicators, the principal component analysis method will be adopted to calculate the intelligence index of listed manufacturing enterprises. Firstly, introduce the distribution of the sample of listed manufacturing enterprises selected in the paper; Secondly, based on principles such as objectivity and data availability, an evaluation index system for the intelligence level of manufacturing enterprises is constructed, and the principal component analysis method is used to measure the intelligence level. Finally, a detailed comparison and analysis of the intelligent upgrade levels of different regions and industries should be conducted.

2.The distribution of samples of listed manufacturing enterprises

China has maintained its position as the world's largest manufacturing country for many consecutive years. While providing a large number of low-cost goods to countries around the world, it has also broadened trade channels and in turn enhanced the vitality and strength of domestic market entities. However, in some key fields and core technologies, there is still a technological gap compared with leading Western countries. The fact that high-end operating systems, intelligent image processing chips, high-precision lithography machines, chip design software, and aviation and Marine engines have not yet achieved domestic substitution has restricted the pace of independent innovation. Especially in recent years, with the adjustment and changes in the industrial structure, the proportion of manufacturing added value in GDP has shown a significant downward trend. Therefore, it is urgent and necessary to promote the intelligent upgrade of manufacturing enterprises to avoid hollowing out(. With the in-depth integration and application of intelligent technologies and industries, the digital economy, characterized by digital industrialization and industrial digitalization, has achieved a nearly linear growth trend. In 2021, the scale of China's digital economy reached a new high, accounting for 39.8% of the GDP. Especially, the COVID-19 pandemic has become a touchstone for the development of the digital economy. Among them, the penetration and empowerment of intelligent technologies in different industries have achieved rapid growth. From 2004 to 2020, the total number of manufacturing enterprises in China grew approximately linearly, with an average annual growth rate of 8.63%. Among them, the number of enterprises undergoing intelligent upgrading increased by 11.77% annually, demonstrating a development trend of the manufacturing industry's transformation and upgrading from low-end manufacturing to high-end intelligent manufacturing(Li and Wang, 2022). This section will mainly introduce the sample distribution of listed manufacturing enterprises.

2.1Research samples and data sources

Process the samples as required by the research: (1) Delete the samples with missing data; (2) Delete the samples that have been ST and PT; (3) As the existence of outliers may have an adverse impact on the regression results, the adopted variables are truncated, and the processing level is selected as 1%. (4) Since the total factor productivity calculated by the DEA-Malmquist index method requires the sample data to be a balanced panel, the sample of listed manufacturing enterprises is processed as a balanced panel. After data processing, 9,840 samples from 820 listed manufacturing enterprises were obtained. The relevant calculation software for this chapter is SPSS25.0.

Year	Manufacturing Value Added in GDP (%)	Digital Economy in GDP (%)
2010	33.00	18.00
2011	33.00	20.00
2012	32.00	22.00
2013	31.00	24.00
2014	30.00	26.00
2015	29.00	28.00
2016	28.00	30.00
2017	28.00	32.00
2018	27.00	34.00
2019	26.00	36.00

Year	Manufacturing Value Added in GDP (%)	Digital Economy in GDP (%)
2020	25.00	38.00
2021	26.00	39.00

Figure 1. Proportion of Added Value of China's Manufacturing Industry and Digital Economy in GDP

2.2 Sample space distribution

In terms of geographical distribution, the sample enterprises are spread across 31 provinces in China. Among them, the number of listed manufacturing enterprises in the eastern, central, western and northeastern regions is 334, 102, 324 and 60 respectively. It can be seen that although the distribution of listed manufacturing enterprises is relatively balanced among regions, there is a serious imbalance within regions. For instance, in the eastern region, Shanghai has the largest number of listed manufacturing enterprises (123), while Fujian Province has the fewest (8). In the western region, Yunnan Province has the largest number of listed manufacturing enterprises (96), while Qinghai Province has the fewest (2). Among the manufacturing listed companies in Northeast China, Jilin Province has the largest number (52), while Heilongjiang Province has the fewest (1).

2.3 Distribution of sample industries

From the perspective of industry distribution, the sample enterprises are widely distributed across 29 major industries, almost covering all the sub-sectors of the manufacturing industry. However, the proportion of enterprises varies significantly among different industries. The industry with the largest number of enterprises is the computer, communication and other electronic equipment manufacturing industry, with a total of 121 enterprises, accounting for 14.76% of the total sample. The number of pharmaceutical manufacturing enterprises ranked second, with a total of 107, accounting for 13.05% of the total sample. The electrical machinery and equipment manufacturing industry ranked third in terms of the number of samples, with a total of 89 enterprises accounting for 10.85% of the total samples. The remaining 26 industries all accounted for less than 10%. Among them, the leather, fur, feather and their products and footwear manufacturing, wood processing and wood, bamboo, rattan, palm and grass products manufacturing, furniture manufacturing, and comprehensive utilization of waste resources manufacturing industries had the fewest samples of listed enterprises. They account for 0.24%, 0.24%, 0.12% and 0.12% respectively. In addition, the total number of enterprises in the seven major categories of high-tech industries amounts to 369, accounting for 45.02%, which also indicates that the overall trend of China's manufacturing industry moving towards a high-end ecological niche of high technology and high quality is strengthening.

Industry	Percentage
Agricultural and sideline food processing industry	14.76%
Food manufacturing industry	9.51%
Beverage, alcohol, and refined tea manufacturing industry	2.68%
Textile industry	0.37%
Textile apparel, clothing, and accessories industry	2.20%
Leather, fur, feather, and their products and footwear industry	1.95%
Wood processing and wood, bamboo, rattan, palm, straw products industry	0.12%

Industry	**Percentage**
Furniture manufacturing industry	0.61%
Paper and paper products industry	13.05%
Printing and recording medium reproduction industry	1.71%
Cultural, educational, sports, and entertainment goods manufacturing industry	2.93%
Petroleum processing, coking, and nuclear fuel processing industry	5.37%
Chemical raw materials and chemical products manufacturing industry	6.71%
Pharmaceutical manufacturing industry	10.85%
Chemical fiber manufacturing industry	5.24%
Rubber and plastic products industry	2.44%
Non-metallic mineral products industry	3.41%
Ferroalloys smelting and rolling processing industry	4.76%
Non-ferrous metal smelting and rolling processing industry	1.10%
Metal products industry	1.59%
General equipment manufacturing industry	2.44%
Specialized equipment manufacturing industry	0.73%
Automobile manufacturing industry	0.37%
Railway, ship, aerospace, and other transportation equipment manufacturing industry	0.24%

Table 2. Industry Distribution Map of Sample Enterprises

3. Measurement of the intelligence level of listed manufacturing enterprises

Based on the concept of intelligent level in CPS theory, this chapter constructs an intelligent level index system for listed manufacturing enterprises by integrating intelligent indicators with traditional indicators. It uses the principal component analysis method with objective weighting to calculate the corresponding intelligent index. Finally, it summarizes and analyzes the intelligent level of listed manufacturing enterprises by region and industry.

3.1 Build an evaluation index system for the level of intelligence

China attaches great importance to the intelligent transformation of enterprises to promote high-quality development of the manufacturing industry. Since 2015, a number of national standards have been piloted and promulgated to evaluate the intelligent development level of enterprises in all aspects. These standards not only include the maturity assessment methods and models for the comprehensive capabilities of intelligent manufacturing, but also cover the value and benefit reference models generated after intelligent transformation, as well as specific evaluation methods for aspects such as the performance of production equipment and the digitalization of the supply chain. The aim is to strengthen guidance on the accelerated integration of intelligent technologies and enterprise applications and enhance the ability to respond to uncertain risks. In 2017, a public service platform for the assessment and evaluation of intelligent manufacturing covering 31 major categories of manufacturing was launched, and the "Intelligent Manufacturing Development Index Report" was regularly released. (Yang et al., 2021) Although these evaluation criteria are all measurement indicators of intelligence at the micro enterprise level, no dedicated database has been established for the statistics of these indicators, and no relevant data has been disclosed in the annual reports of listed companies. Furthermore, most of the standards are descriptive qualitative measurements and lack specific data support. In particular, as an indicator data of industrial robots that directly reflects the level of intelligent development of enterprises, only the national and industry data released by the International Federation of Robotics (IFR) is available, while the specific data of industrial robots at the enterprise level in China is missing. The commonly used indicators of industrial robots often only reflect a single aspect of intelligence. Therefore, the approach of constructing a comprehensive indicator system to measure the intelligence level of manufacturing enterprises can more comprehensively reflect the multi-dimensional development of intelligence than a single indicator. In addition, some scholars have attempted to use the "0-1" dummy variable of "whether the enterprise carried out intelligent upgrading in the current year" to measure the level of intelligence. However, this method is difficult to reflect the "intensity" of the intelligence level. Relying solely on the dummy variable cannot accurately measure the degree or stage of the enterprise's intelligent transformation. Based on this, this paper will construct an evaluation index system for the level of intelligence as shown in Table 1, in accordance with the principles of authenticity, objectivity, continuous comparability and availability for building an evaluation index system, and in combination with the key technical capabilities that intelligence should possess in Chapter Two and the dynamic mechanism of intelligence capabilities in Chapter Three. The specific meanings of each indicator are as follows:

(1) Hardware foundation

The hardware foundation is the physical basis of intelligence. In intelligent workshops and factories, a large number of hardware sensors, Internet devices, etc. are needed to collect, transmit, integrate and process data in the physical world. These hardware foundation conditions not only affect the application efficiency of new-generation information technology, but also influence the process and depth of intelligent upgrading of enterprises. In the article, the original value of electronic devices is selected as the basic hardware proxy index of the hardware foundation. At the same time, drawing on the practices of Qi and CAI (2020), using the text mining method to analyze the manually collected annual reports of sample enterprises, and using the frequency of occurrence of specific keyword 2 as a proxy indicator for intelligent hardware, The frequency of specific keywords appearing in the annual report of the current year can represent the degree of attention an enterprise attaches to intelligent upgrading. The original value of electronic equipment multiplied by the word frequency of intelligent hardware is taken as the hardware basic proxy indicator for the level of intelligent upgrading. This indicator can simultaneously represent the development level of traditional equipment and intelligent equipment.

(2). Software Fundamentals

The software foundation serves as the information basis for intelligence. For manufacturing enterprises to achieve intelligence by integrating, computing and analyzing various data collected from the physical world and transferring them to cyberspace, it relies on the powerful computing capabilities of software. If enterprises adopt ERP systems, CSM systems, CRM systems, MES systems and PLM systems, etc. to complete the intelligent upgrade of procurement, production, inventory, quality and operation management, they cannot do without the support of industrial software. In this paper, the book value of software is selected as the basic software agency indicator of the software foundation. At the same time, it also draws on the practices of Li and Wang (2021), that is, the text mining method is adopted to analyze the annual reports of sample enterprises, and the frequency of occurrence of specific keyword 3 is used as a proxy indicator for intelligent software. The software book value multiplied by the word frequency of intelligent software is taken as the basic agent indicator of the intelligent upgrade level of the software, and this indicator can simultaneously represent the general office

The development level of public software and high-end intelligent software.

(3). Talent foundation

The Fourth Industrial Revolution is manifested in the combination of machine intelligence and human mental labor, which not only enhances the productivity of physical labor but also improves the efficiency of intellectual labor. Therefore, the talent base is the core of intelligence. Both intelligent hardware infrastructure and intelligent software algorithms rely on the progress of knowledge mastered by humans. Talent is the core of scientific and technological progress. High-end talents who master key core technologies determine the breadth and depth of the absorption and diffusion of new-generation information technologies, and are a key factor influencing the intelligent upgrade of manufacturing enterprises. The talent foundation lies in the configuration of hardware and software

The key force for the effective allocation of resources, thus the talent base is a necessary condition for the material base to play its role. The human capital involved in intelligence is reflected in the new thinking, new knowledge and new skills mastered by R&D personnel. The larger the scale of R&D personnel, the more significant the complementary and promoting effect in their professional fields, and the more obvious their promoting effect on the level of intelligence. Therefore, the number of R&D personnel is selected as a proxy indicator to reflect the basic situation of talents in this paper.

(4). Capital base

A capital base is a necessary condition for intelligence. Intelligent transformation requires a large investment in intelligent equipment and talents. However, these high investments cannot be quickly converted into profit growth and efficiency improvement in the short term, which makes enterprises with originally weak capital lack the motivation to implement intelligent transformation. Existing research also shows that the more capital an enterprise has, the more motivated it is to implement intelligent transformation. Therefore, the capital base is an important indicator for measuring intelligence, and R&D expenditure, as a specific manifestation of the capital base, can ensure the smooth progress of R&D work and stimulate the innovative enthusiasm of R&D personnel

To enhance the ability of intelligent upgrading of enterprises through the development of new product technologies, this paper selects research and development expenditure as the agency indicator of the capital basis.

(5). Research and development intensity

The intensity of research and development is expressed by the ratio of R&D expenditure to operating income. The higher the value, the more the enterprise values technological innovation, can adjust its investment direction, and focus internal and external innovation resources on the introduction and absorption of new knowledge and new technologies to guide R&D and production. This is more conducive to establishing a scientific concept of transformation and upgrading and improving the level of intelligence.

(6). Innovation ability

Innovation capacity is expressed by the ratio of R&D personnel to the total number of employees. The higher the proportion of R&D personnel, the more significant the effect of technology diffusion and spillover. At the same time, the R&D personnel of an enterprise can enhance communication and cooperation with research institutes, universities and other institutions by leveraging their own resources, thereby improving the enterprise's ability to carry out collaborative innovation with external resources, which is more conducive to promoting intelligent transformation and upgrading.

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Goal Layer	Indicator	Specific Indicator (Unit)	Attribute
Intelligence Level	Hardware Foundation	Original Value of Electronic Equipment (Yuan) × Frequency of Intelligent Hardware Keywords	Positive
	Software Foundation	Book Value of Software (Yuan) × Frequency of Intelligent Software Keywords	Positive
	Talent Foundation	Software Personnel (People)	Positive
	Capital Foundation	R&D Expenditure (Yuan)	Positive
	Research Intensity	Ratio of R&D Expenditure to Operating Revenue (%)	Positive
	Innovation Ability	Ratio of R&D Personnel to Total Number of Employees (%)	Positive

Table 3. Evaluation Index System for the Intelligence Level of Listed Manufacturing Enterprises

3.2 Principal Component analysis is used to measure the level of intelligence

There is a very obvious correlation among the six indicators in the constructed evaluation index system for the intelligence level of listed manufacturing enterprises, which will cause multicollinearity problems. Principal component analysis is an evaluation method that objectively assigns weights and can eliminate the correlation of indicators. Therefore, this paper uses the software SPSS25.0 to apply principal component analysis to measure the intelligence level of manufacturing enterprises.

(1). KMO and Bartlett spherical inspection

KMO and Bartlett tests were used to verify whether the constructed evaluation index system for the intelligence level of manufacturing enterprises was suitable for principal component analysis. The specific results are shown in Table 4

The measurement of the suitability of KMO sampling		0.707
Bartlett's Test	Approximate Chi-Square	36874.041
	Degrees of Freedom	15.000
	Significance	0.000

Table 4 KMO and Bartlett's test

The relevant results in Table 4 show that the correlation of each indicator at a highly significant level is 0.707, indicating that it is appropriate and proper to use the principal component analysis method to measure the intelligent development level of enterprises.

(2). Extract the main components

The principal components were extracted based on the principle that the eigenvalues are greater than 1 and the cumulative variance contribution is greater than 80%. The results of the eigenvalues and variance contribution of the intelligent level evaluation index system are shown in Table 5.

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	Variance Percentage	Cumulative %	Total	Variance Percentage	Cumulative %
1	2.483	64.924	64.924	2.483	64.924	64.924
2	1.384	17.452	82.375	1.384	17.452	82.375
3	0.866	9.627	92.002			
4	0.578	4.291	96.293			
5	0.478	2.526	98.819			
6	0.212	1.181	100			

Table 5 Eigenvalues and variance contribution rates

As can be seen from Table 5, in the intelligent level index system, the eigenvalues of two principal components are higher than 1, with values of 2.483 and 1.384 respectively. The variance percentages of the two principal components extracted for the intelligent level evaluation index reach 41.384% and 23.066% respectively, and the cumulative variance contribution is 82.375%. It indicates that the two principal components of the intelligent level evaluation index can represent the original six variables.

(3). Calculating the Intelligence Level Index for Listed Manufacturing Enterprises

First, the two principal components of the intelligent level evaluation indicators are named F1 and F2, respectively. Their component matrix is shown in Table 6. The values in Table6 represent the correlation coefficients between the two principal components and the variables of the intelligent level evaluation indicators. The eigenvectors of each indicator are obtained by dividing the values by the square root of the eigenvalues of the principal components, as shown in Table 7.

Table 6 Component Matrix

Variable	**Principal Component F1**	**Principal Component F2**
Z_1 R&D Expenditure	0.821	-0.304
Z_2 Number of R&D Personnel	0.858	-0.071
Z_3 Book Value of Software × Frequency of Intelligent Software Keywords	0.688	-0.353
Z_4 Original Value of Electronic Equipment × Frequency of Intelligent Hardware Keywords	0.359	-0.369
Z_5 Ratio of R&D Expenditure to Operating Revenue	0.418	0.740
Z_6 Ratio of R&D Personnel to Total Number of Employees	0.544	0.692

Table 7 Eigenvector Matrix

Variable	**Principal Component F1**	**Principal Component F2**
Z_1 R&D Expenditure	0.521	-0.259
Z_2 Number of R&D Personnel	0.545	-0.060
Z_3 Book Value of Software × Frequency of Intelligent Software Keywords	0.436	-0.300

Variable	Principal Component F1	Principal Component F2
Z_4 Original Value of Electronic Equipment × Frequency of Intelligent Hardware Keywords	0.228	-0.313
Z_5 Ratio of R&D Expenditure to Operating Revenue	0.265	0.629
Z_6 Ratio of R&D Personnel to Total Number of Employees	0.345	0.588

Secondly, based on this, the expressions of the two principal components of the intelligent level can be written as Equations (3-1) and (3-2):

F1=0.521Z1+0.545Z2+0.436Z3+0.228Z4+0.265Z5+0.345Z6F1=0.521Z1+0.545Z2+0.436Z3+0.228Z4 +0.265Z5+0.345Z6 (Equation 3-1)

F2=−−0.259Z1−0.060Z2−0.300Z3−0.313Z4+0.629Z5+0.588Z6F2=−−0.259Z1−0.060Z2−0.300Z3 −0.313Z4+0.629Z5+0.588Z6 (Equation 3-2)

Finally, by using the eigenvalue of a single principal component divided by the sum of the eigenvalues of both principal components as the weight, the model is obtained as shown in Equation (3-3):

Intelligent Level=2.4832.483+1.384F1+1.3842.483+1.384F2Intelligent Level=2.483+1.3842.483F1 +2.483+1.3841.384F2 (Equation 3-4)

Using Equation (3-3), the comprehensive score value of the intelligent upgrading level for listed manufacturing enterprises can be obtained, which represents the intelligent index of listed manufacturing enterprises.

3.3 Analysis of the results of the intelligentization index of listed manufacturing enterprises

Through the calculation steps in Section 3.2, the intelligentization index of listed manufacturing enterprises can be obtained. Due to the large number of samples, this section only analyzes the differences in the level of intelligentization development in different regions and industries.

3.3.1 Intelligentization level of enterprises in different regions

(1) Horizontal comparison: The average value of the annual intelligentization index of enterprises is sorted from high to low according to the provinces where they are located, as shown in Table 4.6. It can be seen that there are significant differences in the level of intelligentization development among provinces. Among them, the intelligentization level of listed manufacturing enterprises in Beijing, Hubei, and Guangdong is relatively high, reaching 0.519, 0.187, and 0.177 respectively; the intelligentization level of listed manufacturing enterprises in Gansu, Qinghai, and Ningxia in recent years is the lowest, which are -0.620, -0.625, and -0.825 respectively. In terms of the intelligentization level of listed manufacturing enterprises by region, the eastern region is the highest, reaching -0.342, followed by the central region at -0.408, the northeast region ranks third at -0.506, and the western region has the lowest intelligentization level at -0.524.

(2) Vertical comparison: The average value of the enterprise intelligentization index is plotted by year as shown in Figure 4.5. It can be seen that with the development of technological innovation and industrial integration, China's manufacturing intelligentization index shows an overall growth trend, increasing from -1.087 in 2010 to 0.355 in 2021. Although the annual growth trends in various regions are similar, the unbalanced development in the same time dimension is obvious. The intelligentization index from high to low is in the eastern, central, northeast, and western regions, which is consistent with the conclusion of the horizontal comparison. In addition, it can be seen that the intelligentization index of manufacturing enterprises has gone through three different stages. The first stage is from 2010 to 2015,

during which the intelligentization index is at a relatively low level, and the growth rate is almost zero in other years except for a relatively obvious growth rate in 2011; the second stage is from 2015 to 2019, during which the growth rate of the intelligentization index increases significantly. This is related to the incentive of a series of industrial policies issued intensively after the country began to take intelligent manufacturing as the main direction of the national top-level strategic planning in 2015. The strong vane has set off a wave of pilots such as smart workshops, unmanned factories, and intelligent applications across the country, promoting enterprises to stride forward on the new journey of intelligent transformation; the third stage is from 2019 to the present. The intelligentization index is also rising steadily, but the growth rate is slower compared with the second stage. This is related to the impact of the COVID-19 epidemic and the trend of anti-globalization, which have led to insufficient human resources and capital, and the lack of resilience in the industrial chain and supply chain. In particular, the epidemic has exposed the disadvantages such as the risk of infection caused by human gathering and reduced efficiency after recovery, which has also forced enterprises to speed up the deployment and promotion of the "machine replacement" strategy. However, the superposition of the uncertainty and negative impact brought by the epidemic and its promotion effect has slowed down the growth trend of the intelligentization index.

3.3.2 Intelligentization level of enterprises in different industries

The average value of the intelligentization index of manufacturing enterprises is sorted by industry as shown in Figure 4.6. It can be seen that there are significant differences in the intelligentization index among various industries. In particular, the standard deviation of industries with a high level of intelligentization exceeds 1, while the standard deviation of industries with a low intelligentization index is small, indicating that the unbalanced development of enterprises in industries with a high intelligentization index is more significant. The intelligentization index of 7 high-tech industries represented by the computer, communication, and other electronic equipment manufacturing industries (with the highest intelligentization index of 0.665) is generally higher than that of traditional industries. The high-tech industry itself is a test field and incubator of new generation information technology, and it is the first field where new technologies and knowledge are applied, and then diffused to traditional fields, so its intelligentization index level is relatively high. In addition, some traditional industries advocate concepts such as pure manual manufacturing, which leads to a low adoption rate of machinery and equipment, resulting in a low intelligentization index. For example, the leather products industry (with an intelligentization index of -0.84) and the wine and tea manufacturing industry (with an index of -0.668) rank last in terms of intelligentization level. While other traditional industries such as the automobile manufacturing industry have a relatively high level of machinery and electrification. Coupled with the country's strong subsidies for the new energy industry, the integration of intelligent technology and the automobile manufacturing industry has incubated new products and new application scenarios such as intelligent vehicles, vehicle networking, and online car-hailing. The empowerment and penetration of new generation information technology have significantly improved the intelligentization index of the automobile manufacturing industry, with an index of 0.29, ranking third in the industry.

4 Measurement of Total Factor Productivity of Listed Manufacturing Enterprises

Based on the analysis of different efficiency evaluation methods, this section uses the DEA-Malmquist index model to measure the total factor productivity of A-share listed manufacturing enterprises from 2010 to 2021 as a representation of technical efficiency, and summarizes and analyzes the evaluation results.

4.1 Introduction to DEA-Malmquist Index Model

Technical efficiency refers to the state of reaching Pareto optimal efficiency without increasing tangible inputs or reducing outputs under existing resource constraints. Currently, the mainstream methods for measuring technical efficiency in the theoretical circle can be divided into three types according to whether parameters need to be set: the first is parameter-required methods, such as Solow residual method and stochastic frontier method; the second is semi-parametric methods, such as OP and LP methods; the third is non-parametric methods, such as DEA and growth accounting methods. Among them, the first two methods need to set production functions and belong to parametric methods, and when there are random errors in the production function, it is easy to ignore the role of technical efficiency. The DEA-Malmquist index method combines the DEA model and the Malmquist index to measure the technical efficiency of multiple inputs and outputs of homogeneous decision-making units without setting a production function. In addition, this method can reflect the dynamic evolution of technical efficiency in terms of technology and scale economy over time, so this paper chooses the DEA-Malmquist index method, which is more in line with the research reality.

4.2 Index System of Total Factor Productivity of Listed Manufacturing Enterprises

To ensure that the research is in line with the actual production situation of enterprises, the selection of input and output indicators should follow the principles of representativeness, comprehensiveness, and objectivity. Drawing on the practices of Wue (2022) and Ji (2015), the evaluation index system of total factor productivity of listed manufacturing enterprises is constructed as shown in Table 4.1.

Table 4.1 Evaluation Index System of Total Factor Productivity of Listed Manufacturing Enterprises

Type	**Index Name**	**Index Description**
Input Indicators	Net Fixed Assets	It is the original value of enterprise fixed assets minus accumulated depreciation, which can reflect the input of material capital factors of the enterprise.
	Total Number of Employees	Expressed by the total number of employees in the enterprise annually, which can reflect the input of labor factors of the enterprise.
Output Indicators	Return on Main Business Assets	It can reduce the possibility of manual operation and objectively and truly reflect the operating level of the enterprise.
	Operating Income	Expressed by main business income, it is the embodiment of the main operating results of the enterprise and can comprehensively reflect the output level of the enterprise.
	Net Profit	It can reflect the ability of the enterprise to convert inputs into profits.

The number of sample enterprises in this paper is 820, which is more than twice the number of input and output indicators required by the DEA-Malmquist model. The DEAP2.1 software is used to calculate the total factor productivity of enterprises.

4.3 Analysis of Total Factor Productivity Results of Listed Manufacturing Enterprises

Due to space limitations, this section only analyzes the total factor productivity of listed manufacturing enterprises by different regions and industries, and does not further analyze the decomposed efficiency of total factor productivity.

Total factor productivity of enterprises in different regions

(1) Horizontal comparison: The average value of the annual total factor productivity of enterprises is plotted from high to low according to the provinces where they are located. Overall, the average total factor productivity of all provinces shows a positive growth trend, but there are significant differences in the specific growth rates of total factor productivity among different provinces. Among them, the average growth rates of total factor productivity of listed manufacturing enterprises in Yunnan, Xinjiang, and Tianjin are the fastest, ranking the top three, reaching 11.1%, 11%, and 9.7% respectively; the growth rates of listed manufacturing enterprises in Anhui, Hainan, and Qinghai are the slowest, ranking the last three, at 5.4%, 4.8%, and 2.5% respectively. By region, the western region has the fastest growth rate of 8%, the northeast region has a growth rate of 7%, and the central and eastern regions have relatively similar and slow growth rates, 6.8% and 6.9% respectively.

(2) Vertical comparison: It can be seen that overall, China's manufacturing productivity shows a fluctuating growth trend, increasing from the 2010 benchmark to 1.069 in 2021, with an average growth rate of 6.9%. Similar to the development of intelligentization level, it has also gone through three stages: the first stage is from 2010 to 2015, during which total factor productivity was in a fluctuating state with almost no growth. For example, although all four regions had positive growth from 2010 to 2011, the growth rate was not large, while the growth rate decreased from 2011 to 2012, especially in the central region with the largest decline. Other years can be analyzed similarly and will not be repeated; the second stage is from 2015 to 2019, during which the growth rate of total factor productivity increased significantly, which may be related to the incentive of a series of industrial policies issued intensively by the country starting in 2015, and intelligentization positively promoted the growth of enterprise total factor productivity;(the third stage is from 2019 to the present. After a slight decline in total factor productivity from 2019 to 2020, it ushered in a significant growth in 2020-2021, which is related to the impact of the COVID-19 epidemic that broke out at the end of 2019. The outbreak of the epidemic forced enterprises to carry out intelligent upgrading, which in turn optimized resource allocation, thereby improving total factor productivity.

Total factor productivity of enterprises in different industries

The average value of total factor productivity of listed manufacturing enterprises is sorted by industry from high to low. It can be seen that from 2010 to 2021, except for the leather, fur, feather and related products and footwear industry, which had a 0.2% decline in average total factor productivity, all other industries achieved positive growth. Among them, the comprehensive utilization of waste resources industry had the largest average growth rate of 23%; other manufacturing industries and agricultural and sideline food processing industries ranked second and third in total factor productivity, with average growth rates of 6.8% and 6.6% respectively; while the rubber and plastic products industry, chemical fiber manufacturing industry, and petroleum processing, coking and nuclear fuel processing industry had the slowest growth rates of total factor productivity, ranking the last three, with average growth rates of 2%, 1.9%, and 0.1% respectively. In addition, the growth rate of total factor productivity of the 7 categories of high-tech industries is significantly lower than that of traditional industries, which may be because the resource allocation and input-output level of high-tech industries themselves were originally at a high level, resulting in a slower marginal growth rate.

5. CONCLUSION

This study, by constructing an intelligent level evaluation system and combining with the calculation of total factor productivity, conducted an in-depth analysis of the intelligent development characteristics and efficiency performance of listed manufacturing enterprises in China. The main conclusions are as follows:
The construction and calculation of the intelligent level evaluation system effectively reflect the actual development status of enterprises. Based on an evaluation system of six indicators including hardware foundation, software foundation, and talent foundation, combined with principal component analysis, the level of enterprise intelligence has been successfully quantified. Among them, indicators such as the product of the original value of electronic devices and the frequency of keywords for smart hardware, as well as the product of the book value of software and the frequency of keywords for smart software, take into account the development levels of both traditional and smart devices, making up for the deficiency that a single indicator is difficult to reflect the "intensity" of intelligence, and providing a referenceable quantitative tool for subsequent research.

The level of intelligence in the manufacturing industry shows the characteristics of "overall improvement and significant differences". From a temporal perspective, the intelligence index rose from -1.087 to 0.355 from 2010 to 2021, confirming the continuous advancement of intelligent upgrading in China's manufacturing industry. Moreover, the impact of the national top-level strategy in 2015 and the post-2019 pandemic on the growth rate was significant, demonstrating the crucial role of policies and the external environment. From the perspectives of space and industry, the pattern of the eastern region leading and the western region lagging behind is obvious. This is closely related to the advantages of technology, capital and talent aggregation in the eastern region. In terms of industry, the intelligence level of high-tech industries (such as computer and communication equipment manufacturing) far exceeds that of traditional industries. However, among traditional industries, those that advocate pure manual manufacturing (such as the leather products industry) have the lowest intelligence level, reflecting the constraints of industrial attributes and the willingness to apply technology on the intelligentization process.

There is a phased and structural connection between the growth of total factor productivity and intelligent development. The overall average annual growth rate of total factor productivity was 6.9%. Although the regional and industry differences were not entirely consistent with the level of intelligence (for instance, the growth rate of total factor productivity in the west was higher than that in the east), the two were highly consistent in their development stages (both experienced acceleration around 2015 and adjustment after 2019), confirming the potential driving effect of intelligent upgrading on efficiency improvement. Meanwhile, the phenomenon that the marginal growth rate of total factor productivity in high-tech industries is lower than that in traditional industries indicates the need to pay attention to the efficiency improvement bottleneck in high-base industries and break through the growth ceiling by deepening intelligent applications.

In response to regional differences, more investment should be made in intelligent infrastructure and talent support in the central and western regions as well as the northeastern region to narrow the "digital divide". In response to industry differences, subsidies for intelligent transformation should be provided to traditional industries (especially those that rely on manual labor) to promote the replacement of human workers with machines and the diffusion of technology. For high-tech industries, they should be guided to transform towards more advanced intelligent applications (such as new models of intelligent manufacturing) to break through the bottleneck of marginal growth rate. Future research can further expand the sample range and deeply explore the specific mechanism of the impact of intelligence on total factor productivity, providing more precise theoretical support for the high-quality development of the manufacturing industry.

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