**Frontiers in Business, Economics and Management**
ISSN: 2766-824X | Vol. 14, No. 2, 2024

# Has the Development of Digital Technology Promoted the Efficiency of Logistics Enterprises?

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**Abstract:** Digital technology is a new driving force to promote the evolution of industrial chain and value chain, can the logistics industry realize quality and efficiency through the empowerment of digital technology? This article utilizes the annual report data of logistics enterprises from 2012 to 2021, constructs and measures a dictionary of digital technology development level of logistics enterprises based on Python, and uses BCC model and Malmquist index model to analyze and group comparison the operational efficiency of sample enterprises, in order to test the impact of digital technology development level on the operational efficiency of logistics enterprises.. The results of the study show that (1) with the improvement of the development level of digital technology of logistics enterprises, the static efficiency represented by comprehensive efficiency, pure technical efficiency and scale efficiency have all gained a significant improvement, and the number of effective companies in DEA is positively proportional to the level of digital technology; (2) in terms of the dynamic efficiency represented by technological progress and total factor productivity, the above positive relationship is also significant, especially in 2017 After 2017, the "efficiency" effect is very obvious, indicating that with the increase in the breadth and depth of the application of digital technology in the logistics industry, the effect of improving the operational efficiency of logistics enterprises will be further strengthened.

**Keywords:** Digital technology; Artificial intelligence; Logistics enterprises; Efficiency; DEA.

## 1. Introduction

With the increasing progress of artificial intelligence, cloud computing, blockchain, and big data technology, the impact of digital technology on industry development has become increasingly profound [1]. In this context, developed Western countries have proposed to vigorously promote the digital transformation of traditional industries, and the Chinese government has also introduced relevant policies to create a favorable macro environment. Especially in May 2022, the General Office of the State Council issued the "14th Five Year Plan for Modern Logistics Development", which clearly stated that promoting logistics quality improvement, efficiency enhancement, and cost reduction is an important task for the development of modern logistics in the current period.

The digital revolution is profoundly affecting various industries, and the logistics sector, as an important link supporting supply chain operations, is also facing the impact of digital technology comprehensively. According to reports from the National Industrial Information Security Development Research Center and Accenture Business Research Institute, the traditional retail and logistics industry has made significant progress in digitalization and successfully entered the first tier of digital maturity [2]. The logistics industry hopes to optimize industry factors better through digital technology, and thereby play a promoting role in reducing costs and increasing efficiency in the industry. However, the application of digital technology in China's logistics industry is still in its early stages [3]. How to seize the technological dividend, deeply promote the construction of modern digital logistics systems, and truly achieve cost reduction and efficiency increase in the industry has become an urgent problem. Although digital technology is accelerating its integration into logistics activities and has a wide-ranging impact, there is a clear research gap on whether it can effectively empower industry efficiency. In view of this, this article takes the data of China's A-share logistics industry listed companies from 2012 to 2021 as the research sample, uses text mining methods to extract keywords related to digital technology from the annual reports of logistics enterprises using Python programming language to construct a measurement index system for the level of digital technology development. The DEA model and Malmquist index are used to describe the operational efficiency of the sample enterprises, and the relationship between the level of digital technology development of enterprises and the operational efficiency of enterprises is explored. Finally, it is tested whether the level of digital technology development truly promotes the efficiency improvement of logistics enterprises.

## 2. Literature Review

### 2.1. Relevant Research on Digital Technology

Digital Technology is a combination of digital technology and intelligent technology, which integrates elements from such technological fields as cloud computing, big data, Internet of Things, blockchain and 5G. Meanwhile, it covers intelligent technologies such as intelligent robots, image recognition, speech understanding, natural language processing, machine learning and neural networks. Scholars' understanding of digital technology is constantly changing and deepening. In the early days, most scholars believed that digital technology was just a tool to speed up and improve the efficiency of existing work and provide better data management and information services. However, with the continuous innovation and development of digital technology, people are beginning to realize that digital technology is not only a "tool", but also a transformative technology that can influence production methods, management methods, organizational forms and other aspects. The application of digital technology has triggered a wide range of social changes and structural reconstruction, promoted the change of business model, accelerated industrial intelligence and transformation and upgrading. Therefore, scholars' views on digital technology are increasingly inclined to regard digital technology as the "engine" that drives the entire society, economy and culture to change. The initial stage of digital technology mainly refers to basic technologies such as computer technology and information technology [4], which is marked by the wide application of information and communication technology (ICT) [5].

Regarding the scope of digital technology, Bharadwaj et al. argue that "digital technology is a combination of information, computing, communication and connectivity technologies" [6]. Through further development, Sebastian et al. provide a clearer articulation of digital technologies, i.e., social related technologies, mobile technologies, analytics, cloud technologies, and IoT technologies, such as Big Data, Cloud Computing, Blockchain, IoT, Artificial Intelligence, and Virtual Reality technologies [7].Obukhova et al. advocate that companies need to adopt new technological approaches to transform traditional business processes such as communication, distribution and customer relationship management with digital technologies [8]. Digital Technology, i.e., integrates technologies from various fields of digitalization such as cloud computing, big data, IoT, blockchain, 5G, etc., and at the same time covers intelligent technologies marked by intelligent robots, image recognition, speech understanding, natural language processing, machine learning, and neural networks. Scholars at home and abroad usually refer to digital technologies such as big data, blockchain, Internet of Things, and artificial intelligence as digital technologies to cope with the convergence trend of digitization and intelligence [9].

### 2.2. Impact of Digital Technology on the Operational Efficiency of Logistics Enterprises

Although the academic community has not conducted extensive research on the relationship between digital technology and enterprise operational efficiency, the economic effects brought by the application of digital technology in enterprises have always been the focus of researchers. Under the framework of resource-based theory, digital technology, with its data processing and analysis capabilities, is considered an indispensable production factor for modern enterprise operations. It can be introduced into the production and operation system of enterprises to enhance resource allocation and improve production efficiency. The literature indicates that integrating digital technology into production and operation systems can help improve decision-making processes and enhance overall operational efficiency. Han Xiuzhi et al.'s research shows that the application of big data technology in the tracking, storage, and transportation of fresh fruits can significantly improve transportation efficiency [10]. Chen Yongxian et al. emphasized the importance of using sensors to collect production data and establish models for more accurate planning and scheduling of production. These applications not only improve production efficiency but also increase production quality [11]. Li Yichen pointed out that big data technology provides logistics enterprises with opportunities to process complex data, optimize supply chains, improve customer satisfaction, and reduce operating costs [12]. However, it also poses challenges on how to effectively integrate these technologies into the daily operations of enterprises. Research by Tian Chen and others has shown that artificial intelligence technology can significantly improve delivery efficiency and accuracy [13]. The application of this technology can eliminate information silos, achieve seamless sharing of logistics information, and ensure the smoothness and accuracy of information flow, thereby breaking through the limitations of human resources [14]. Jinbei has confirmed that digital technology plays an important role in strengthening the integration of organizational capital and capabilities in enterprises by introducing the theory of organizational capital into analysis [15]. In addition, Shan Yu et al. proposed that the success of digital transformation lies not only in the adoption of technology and changes in business models, but also in the professionalism and cooperation of the business personnel who carry out these changes, which provides the possibility to fundamentally achieve change from organizational structure and business models [16]. Kayikci pointed out that digital technology can significantly reduce logistics costs, shorten delivery times, and simultaneously reduce delay risks and inventory, enhancing the reliability and flexibility of the supply chain [17]. In addition, Hofmann and Osterwalder discussed the opportunities that digital technology brings to third-party logistics companies, including providing customized services and cloud logistics services [18].

By analyzing existing literature, we can discover the widespread application of digital technologies such as big data and artificial intelligence in various aspects of logistics enterprises, and how these technologies have a positive impact on operational efficiency as advanced production factors. The above research indicates that although the direct relationship between digital technology and the operational efficiency of logistics enterprises has not been widely established and empirically tested, these technologies have shown significant potential for improving quality and efficiency in multiple aspects such as production planning, transportation, data processing, and supply chain management. However, there is still a lack of quantitative research results and evidence on whether the development level of digital technology can truly promote the improvement of operational efficiency in logistics enterprises.

## 3. Evaluation of Operational Efficiency of Logistics Enterprises

### 3.1. Efficiency Evaluation Model

#### 3.1.1. BCC Model

DEA is a methodology that uses technology to measure performance and a non-parametric approach to the production frontier methodology that can assess the relative efficiency of stakeholder decision-making and policy formulation. Operational efficiency, on the other hand, can be defined as the rate at which a logistics firm converts various inputs into outputs in a given time period, which means that logistics firms can improve efficiency by optimizing the proportionality of inputs to outputs in their operations. Generally speaking, the lower the inputs, the higher the operational efficiency; and the more the outputs, the higher the operational efficiency. Therefore, logistics companies can improve operational efficiency and achieve higher performance levels by reducing inputs or increasing outputs. Among many DEA models, CCR [19] and BCC [20] models are two of the most classic and commonly used approaches. the CCR model assumes that the reward per unit of scale is constant, but there are inconsistencies with the actual situation; while the BCC model assumes that the reward per unit of scale is variable. In short, the BCC model is a commonly used method to measure the technical efficiency of production units, which is more flexible than the CCR model and can portray technical efficiency in a more refined way. With the BCC model, the pure scale efficiency of decision-making units can be derived, and this method is suitable for evaluating the efficiency of listed logistics companies.

#### 3.1.2. Malmquist Exponential Modeling

In 1994, FARE et al [21], based on Cave, proposed a measurable productivity change index Malmquist model, which is an efficiency evaluation method based on Data Envelopment Analysis (DEA) to measure the efficiency change of decision-making units (DMUs) and the overall efficiency change from a dynamic perspective. It combines the concepts of the DEA model and the Malmquist index and aims to analyze the efficiency changes and technical progress of DMUs at two points in time (usually two different time periods). The Malmquist index measurement model from period t to period t+1 is as follows:

$$\boldsymbol{TfPh} = \boldsymbol{M}(\boldsymbol{X}^t, \boldsymbol{Y}^t) = \frac{\boldsymbol{D}^{t+1}\ (x^{t+1}, y^{t+1})}{\boldsymbol{D}^t(x^t, y^t)} * \left[\frac{\boldsymbol{D}^t\ (x^{t+1}, y^{t+1})}{\boldsymbol{D}^t(x^t, y^t)} * \frac{\boldsymbol{D}^{t+1}\ (x^{t+1}, y^{t+1})}{\boldsymbol{D}^{t+1}(x^t, y^t)}\right]^{\mathbf{1/2}} \quad (1)$$

## 3.2. Input-output indicator system

#### 3.2.1. Sample Data

The sample is selected based on the "transportation, storage and postal industry" defined by the 2012 version of the industry classification of the Securities and Futures Commission (SFC). As of December 2021, there are 117 A-share logistics companies listed in Shanghai and Shenzhen. In order to ensure the reliability of the research results, the companies with abnormal financial status such as gearing ratio less than 1, ST, SST, etc. and the companies with missing yearly data are excluded, and finally 48 listed logistics companies are selected as samples, and the data used are all from CSMAR database, as shown in Table 1.

**Table 1.** Stock Code and Name of Sampled Enterprises

| Stock code | Enterprise name | Stock code | Enterprise name |
|---|---|---|---|
| 000088 | Yantian port | 600106 | Chongqing Road and Bridge |
| 000089 | CITIC Hai Direct | 600125 | Tielong Logistics |
| 000090 | Guangdong Expressway A | 600190 | Jinzhou Hong Kong Stocks |
| 000091 | Zhuhai Port | 600233 | Yuantong Express |
| 000092 | Hunan Investment | 600269 | Ganyue Expressway |
| 000093 | Beibu Gulf Port | 600279 | Chongqing Harbor |
| 000094 | Dongguan Holdings | 600350 | Shandong Expressway |
| 000095 | Urban Development Environment | 600377 | Ninghu Expressway |
| 000096 | Modern Investment | 600428 | COSCO Hai Te |
| 000097 | Xiamen Port Affairs | 600548 | Shenzhen Expressway |
| 002040 | Port of Nanjing | 600611 | Mass Transportation |
| 002041 | Yunda Shares | 600650 | Jinjiang Online |
| 002042 | Strait Corporation | 600662 | Foreign Service Holdings |
| 002043 | Sf Holdings | 600717 | Tianjin Port Stocks |
| 002044 | Fulin Transportation Industry | 600787 | Zhongchu Shares |
| 002045 | Hengji Daxin | 600897 | Xiamen Airport |
| 002046 | Three Gorges Tourism | 601000 | Tangshan Port Collection |
| 300240 | Freda | 601006 | Daqin Railway |
| 600012 | Wantong Expressway | 601008 | Lianyungang |
| 600017 | Rizhao Port | 601018 | Ningbo Port |
| 600018 | Shanggang Group | 601107 | Chengdu and Chongqing |
| 600020 | Zhongyuan Expressway | 601188 | Longjiang Transportation |
| 600033 | Fujian Expressway | 601518 | Jilin Expressway |
| 600035 | Chutian Transportation | 601880 | Liaogang Stock |

#### 3.2.2. Indicator Selection

In the context of digitalization, the operation of logistics enterprises covers various logistics activities such as transportation, warehousing, distribution, packaging and value-added information. In order to measure the efficiency of these activities, we need to select indicators that can accurately reflect the direct inputs and outputs of these activities. In constructing the indicator system, we base our selection on the evaluation indicators of historical research and the principles of science, system, operability and generality. The input indicators cover human, material and financial resources, and the output indicators are divided into two categories: daily operations and assets. Summarizing the above principles, we select an appropriate number of input and output indicators [22-24] as the evaluation index system for the operational efficiency of logistics enterprises, as shown in Table 2.

**Table 2.** Evaluation indicators of operational efficiency of logistics enterprises

| | Primary indicators | Secondary indicators | Explain |
|---|---|---|---|
| Evaluation index system of operational efficiency of logistics enterprises | Input indicators | Number of employees | Includes only employees who have signed labor contracts with the enterprise |
| | | Net asset value | The sum of net fixed assets and intangible assets |
| | | Business costs | Includes main operating costs and other operating costs |
| | | Overhead | Various costs incurred in organizing and managing production operations |
| | Output indicators | Net profit | Difference between total profit and income tax expense |
| | | Revenues | Includes main operating costs and other operating costs |

#### 3.2.3. Treatment of Indicators

Since the DEA model specifies that the data are non-negative, but the output indicators have a negative net profit of the company, so it is necessary to normalize the selected parameters, so that the data obtained from the processing is in the range of 0~1. Normalization can eliminate the scale and variability between the data, make the weight of each indicator more balanced, and make the range of values of different indicators consistent. In this way, the normalized data can more accurately measure the performance of each DMU and maintain the stability of the relative relationship in the evaluation process. Data normalization does not change the relativities among DMUs, so it does not affect the final evaluation results. Therefore, normalization of data is a very important step in the evaluation of DMU efficiency to ensure the reliability and accuracy of the evaluation results. The processing method is as follows:

$$Y = \frac{Xi - Ximin}{Ximax - Ximin} * 0.9 + 0.1 \tag{2}$$

## 3.3. Evaluation results of operational efficiency of logistics enterprises

#### 3.3.1. Static Efficiency Analysis Based on BCC Modeling

In this paper, BCC model is adopted, and the processed index data are substituted into DEAP2.1 software, and the comprehensive technical efficiency, pure technical efficiency and scale efficiency of 48 listed logistics companies are listed in the table, as shown in Table 3. In order to explore the development trend of operational efficiency of these companies in the period of 2012-2021, the static analysis of operational efficiency was carried out, as shown in Table 3.

As shown in the table, among the 48 logistics listed companies from 2012 to 2021, the average comprehensive efficiency value of the sample companies is 0.738, which is generally low. This means that the vast majority of logistics companies have the potential to improve operational efficiency. The average pure technical efficiency value is 0.851, indicating that there is still nearly 15% room for improvement in theory. The average scale efficiency value is 0.867, which is the highest among the three efficiencies.

The comprehensive efficiency measures the overall efficiency of 48 logistics companies. According to Table 3, the comprehensive efficiency of logistics listed companies in China has shown a gradual increase from 2012 to 2021, except for a significant increase in 2015 and 2020. Due to the fact that comprehensive efficiency is equal to the product of pure technical efficiency and scale efficiency, the trend of average pure technical efficiency and average comprehensive efficiency is consistent. After 2016, the overall average scale efficiency is higher than the average pure technical efficiency, indicating that after 2016, the development focus of China's listed logistics enterprises mainly focuses on expanding enterprise scale, with relatively small improvement in technology and management level, resulting in pure technical inefficiency leading to overall technical inefficiency. That is to say, logistics companies are more inclined to expand their business scale, while the improvement in technology and management is relatively limited, which leads to a lack of pure technical efficiency and thus affects the overall overall overall efficiency level. Therefore, the improvement of pure technical efficiency can more effectively improve the operational efficiency of logistics enterprises than controlling the scale of the enterprise.

**Table 3.** Average static operational efficiency, 2012-2021

| Year | Average combined efficiency | Average pure technical efficiency | Average scale efficiency |
|---|---|---|---|
| **2012** | 0.716 | 0.867 | 0.826 |
| **2013** | 0.690 | 0.844 | 0.817 |
| **2014** | 0.687 | 0.857 | 0.802 |
| **2015** | 0.738 | 0.878 | 0.841 |
| **2016** | 0.694 | 0.829 | 0.837 |
| **2017** | 0.750 | 0.845 | 0.887 |
| **2018** | 0.748 | 0.838 | 0.893 |
| **2019** | 0.763 | 0.830 | 0.919 |
| **2020** | 0.804 | 0.885 | 0.908 |
| **2021** | 0.788 | 0.841 | 0.937 |

#### 3.3.2. Dynamic Efficiency Analysis Based on the Malmquist Index

In order to more accurately evaluate the efficiency progress of enterprises, there are many limitations in only evaluating static efficiency. Therefore, this section uses the DEA Malmquist model from DEAP2.1 software for calculation. Through the application of this model, we have obtained corresponding results, as shown in Table 4.

According to Table 4, the overall average change in total factor productivity reached 1.034, with an annual average growth of 3.4%, indicating an overall upward trend in the operational efficiency of listed logistics enterprises; The annual average growth rate of the technological progress index is 0.4%, and the technological efficiency has decreased by 0.3%. However, between 2012 and 2013, despite significant growth in technological progress, technological efficiency slightly decreased, leading to a decrease in total factor productivity. Between 2015 and 2016, total factor productivity reached its lowest point at 0.957. Although technological progress reached a level of 1.001 during this period, technological efficiency significantly declined to 0.956. Therefore, the decrease in total factor productivity during this period is mainly due to the decrease in technological efficiency. In other words, although technological progress has improved, the decrease in technological efficiency has affected total factor productivity, indicating that the logistics industry still has shortcomings in technology application.

After experiencing a trough from 2019 to 2020, the Technology Progress Index rebounded strongly from 2020 to 2021. Similarly, total factor productivity bottomed out from 2019 to 2020, previously peaking from 2016 to 2017, and later showing signs of recovery from 2020 to 2021. These changes are related to the interaction between external environment and government policies. Since 2017, the logistics industry has widely introduced new technologies such as artificial intelligence and big data, injecting vitality into the industry's development. During the global pandemic, government support policies have further promoted technological innovation and the development of digital technology to improve transportation efficiency and service quality. Therefore, logistics companies should closely monitor technological development trends and actively improve their technological level to cope with future competition and development challenges.

**Table 4.** Malmquist Index and Decomposition of Listed Logistics Companies, 2012-2021

| Year | Techni-cal efficie-ncy change index | Index of change in techno-logical progre-ss | Index of change in pure technic-al efficie-ncy | Scale efficie-ncy change index | Total factor produc-tivity change index |
|---|---|---|---|---|---|
| **2012-2013** | 0.995 | 1.005 | 0.997 | 0.998 | 1.000 |
| **2013-2014** | 1.001 | 1.002 | 1.000 | 1.001 | 1.003 |
| **2014-2015** | 1.000 | 1.003 | 1.001 | 0.999 | 1.003 |
| **2015-2016** | 0.993 | 1.003 | 0.997 | 0.996 | 0.996 |
| **2016-2017** | 0.989 | 1.032 | 0.998 | 0.992 | 1.021 |
| **2017-2018** | 0.991 | 1.012 | 1.000 | 0.991 | 1.003 |
| **2018-2019** | 1.003 | 0.996 | 0.998 | 1.005 | 0.999 |
| **2019-2020** | 1.019 | 0.969 | 1.006 | 1.013 | 0.988 |
| **2020-2021** | 0.985 | 1.036 | 0.992 | 0.993 | 1.021 |
| **Aver-age value** | 0.997 | 1.006 | 0.999 | 0.999 | 1.004 |

# 4. The Influence of the Development Level of Digital Technology on the Operational Efficiency of Logistics Enterprises

## 4.1. The Level of Digital Technology Development in Logistics Enterprises

This article adopts the reference of Wu Fei et al. [25] on the measurement method of digital transformation in manufacturing enterprises, and evaluates the application of digital technology in logistics enterprises based on this. Specifically, by crawling the financial annual report data of logistics companies listed on the Shanghai Stock Exchange and Shenzhen Stock Exchange from 2012 to 2021, and extracting policy texts related to the logistics industry from the State Council policy document library on the Chinese government website, Python and text mining technology were used to analyze the keywords related to digital transformation in these annual reports. Based on the analysis, digital technology is divided into five dimensions according to its nature, application scenarios, and technological characteristics, combined with the opinions and suggestions of relevant experts, as shown in Table 5.

**Table 5.** Keywords of Digital Technology for Logistics Enterprises

| Keyword dimension | Keyword quantitative indicators |
|---|---|
| **Intelligent Sensing and Recognition** | Smart Sensors, Image Recognition, Face Recognition, Barcode Recognition, RFID, Sensors, Infrared Sensing, RF Systems, Smartphones, Environmental Monitoring |
| **Automation and Control** | Automatic Control, Automatic Detection, Automatic Identification, Robotics, Automated Guided Vehicle, Autonomous Mobile Robots, Drones, Unmanned Machines, Unmanned Forklifts, Unmanned Sorting Vehicles, Unmanned Tractor Trailers, Rail-Guided Automated Vehicles, Mobile Application Technology, Monitoring Technology, Data Processing, Data Interchange, Intelligent Warehousing, Milkrun Cyclic Pickup |
| **Data and Communications** | ICT, Internet, Interconnection, Warehouse Management System, GPS, GPRS, Geographic Information System, Electronic Toll Collection System, Intelligent Transportation System, Electronic Data Interchange, Data Analysis, Data Sharing, Data Management, Data Mining, Data Transmission, Data Visualization, Big Data Analysis, IT, APP POS, IC Card |
| **Intelligent Algorithms and Technologies** | Intelligent Algorithms, Augmented Reality, Virtual Reality, Mixed Reality, 5G, 3D Printing, Intelligent Algorithms, Artificial Intelligence Technology, Logistics Monitoring Technology |
| **Internet of Things and Cloud Computing** | IoT, Cloud Computing, Blockchain, Edge Computing, Artificial Intelligence Internet of Things |

According to the constructed logistics enterprise digital technology dictionary, the keywords for a total of 10 years from 2012 to 2021 are extracted, and since the total number of keywords obtained has a right bias, the direct bias as the degree of transformation will be larger. Therefore, in accordance with the research of Wu Fei and other scholars, it is logarithmized so as to obtain the overall index for portraying the digital technology of logistics enterprises, and the value of this index is proportional to the degree of digital technology of enterprises, as shown in Table 6.

Divide the digital technology level of 48 listed logistics companies from 2012 to 2022 into two parts based on the average value. As the average value is 1.252, companies with digital technology indicators between 0 and 1.252 are classified as samples with low digital technology level. Companies with digital technology indicators greater than 1.252 are classified as samples with high digital technology level, resulting in 19 logistics companies with high digital technology and 29 logistics companies with low digital technology. This indicates that in the past decade, some logistics companies have performed outstandingly in the application and development of digital technology, while others have performed relatively poorly. This classification can help us better understand the differences and leading levels of digital technology among different logistics companies.

**Table 6.** Descriptive Statistics of Numerical Intelligence Technology Levels

| Variant | Sample size | Avera-ge value | Stand-ard deviati-on | Maxi-mum value | Minim-um value |
|---|---|---|---|---|---|
| DIG | 480 | 6.650 | 17.108 | 186 | 0 |
| Ln(DIG+1) | 480 | 1.252 | 1.098 | 5.231 | 0 |

## 4.2. The Impact of Digital Technology Development Level on Operational Efficiency

To describe the relationship between the level of digital technology development and logistics efficiency, we set the level of digital technology development as a categorical variable and divided it into low-level and high-level groups. Using grouping statistical methods, we described the relationship between the level of digital technology development and static and dynamic logistics efficiency, respectively. The results are shown in Tables 7 and 8.

### 4.2.1. 1. Static Efficiency

In terms of static operational efficiency, scholars usually choose comprehensive efficiency or pure technical efficiency for a single analysis. In this article, comprehensive efficiency, pure technical efficiency, and scale efficiency are selected to describe the static operational efficiency.

**Table 7.** The proportion of companies that achieve effective static operational efficiency

| Ye-ar | Crste=1 Company proportion | | Vrste=1 Company proportion | | Scale=1 Company proportion | |
|---|---|---|---|---|---|---|
| | High level | Low level | High level | Low level | High level | Low level |
| 2012 | 26.32% | 6.90% | 36.84% | 10.34% | 26.32% | 6.90% |
| 2013 | 26.32% | 3.45% | 42.11% | 13.79% | 26.32% | 3.45% |
| 2014 | 31.58% | 10.34% | 42.11% | 20.69% | 31.58% | 10.34% |
| 2015 | 21.05% | 20.69% | 42.11% | 20.69% | 21.05% | 20.69% |
| 2016 | 26.32% | 20.69% | 47.37% | 27.59% | 26.32% | 20.69% |
| 2017 | 26.32% | 13.79% | 47.37% | 20.69% | 31.58% | 17.24% |
| 2018 | 26.32% | 17.24% | 47.37% | 24.14% | 31.58% | 17.24% |
| 2019 | 31.58% | 17.24% | 52.63% | 17.24% | 31.58% | 20.69% |
| 2020 | 26.32% | 13.79% | 36.84% | 13.79% | 26.32% | 17.24% |
| 2021 | 26.32% | 17.24% | 47.37% | 20.69% | 26.32% | 24.14% |

The grouping statistical results in terms of static efficiency are shown in Table 7. It can be seen that the number of companies achieving effective levels varies under different levels of digital technology and efficiency, and the overall proportion of effective companies is relatively low. At a high level of digital technology development, the proportion of logistics companies with fully effective DEA is relatively stable, fluctuating from 21% to 32%; However, at a low level of digital technology development, the proportion of logistics companies that are fully effective in DEA fluctuates between 3% and 21%. Among them, the proportion of high digital technology level effective companies in pure technical efficiency is the highest, but only in 2019 did the proportion of effective companies exceed half; Except for the lowest proportion of effective companies in 2012 and 2020, which reached 36.84%, the proportion of effective companies in all other years fluctuated between 42% and 53%. Under high levels of digital technology development, the proportion of companies with completely effective scale efficiency fluctuates between 21% and 32%, while under low levels of digital technology development, the proportion of companies with completely effective scale efficiency fluctuates between 3% and 24%, similar to the proportion range of comprehensive efficiency.

It can be clearly seen that in terms of comprehensive efficiency, pure technical efficiency, and scale efficiency, logistics enterprises with high levels of digital technology have a higher proportion of effective companies every year than those with low levels of digital technology, indicating that the level of digital technology is directly proportional to the number of effective companies. In other words, the development of digital technology helps logistics enterprises achieve "efficiency enhancement".

### 4.2.2. Dynamic efficiency

In terms of dynamic operational efficiency, in addition to the total factor productivity commonly used by scholars, this article will also consider the impact of technological progress.

**Table 8.** The proportion of companies achieving effective dynamic operational efficiency

| Year | Techch≥1 Company proportion | | Tfpch≥1 Company proportion | |
|---|---|---|---|---|
| | Higher level of Digital Technol-ogy | Low level of Digital Technolo-gy | Higher level of Digital Technology | Low level of Digital Technology |
| **2012-2013** | 68.42% | 86.21% | 52.63% | 41.38% |
| **2013-2014** | 68.42% | 86.21% | 47.37% | 72.41% |
| **2014-2015** | 10.53% | 13.79% | 52.63% | 55.17% |
| **2015-2016** | 89.47% | 86.21% | 63.16% | 51.72% |
| **2016-2017** | 26.32% | 51.72% | 63.16% | 79.31% |
| **2017-2018** | 78.95% | 68.97% | 63.16% | 51.72% |
| **2018-2019** | 47.37% | 41.38% | 63.16% | 44.83% |
| **2019-2020** | 15.79% | 0% | 31.58% | 31.03% |
| **2020-2021** | 94.74% | 86.21% | 78.95% | 68.97% |

The grouping statistical results between the development level of digital technology and dynamic efficiency are shown in Table 8. The results show that compared to the proportion of companies with static operational efficiency, the proportion of companies with dynamic operational efficiency is higher, with most effective companies accounting for over 50%. A significant feature indicates that the impact of digital technology on dynamic efficiency exists at a critical time point in 2017. Since 2017, the proportion of effective companies with high levels of digital technology development has been higher than that with low levels of digital technology development. This phenomenon coincides with an important period of digital, information-based, and intelligent transformation in the logistics industry. The active investment of capital in various fields, the rise of China's logistics development to the national strategic level, and the continuous promotion of policies have all provided favorable conditions for the development of the logistics industry. The deepening of deleveraging policies in the financial sector has further optimized the funding environment for the logistics industry. The development speed of related fields has exceeded the growth rate of the national economy, providing a rare opportunity for the transformation and upgrading of the logistics industry. Meanwhile, innovative technologies such as artificial intelligence, big data, cloud computing, and blockchain are rapidly developing and widely applied in the logistics industry.

Before 2017, there were significant fluctuations in the impact of the development level of digital technology on the efficiency of technological progress and total factor productivity, which did not result in a stable improvement effect. After 2017, it gradually became stable and clear. With the improvement of digital technology development level, the proportion of logistics enterprises with technological progress and total factor productivity growth steadily increased. This phenomenon indicates that after 2017, digital technology has become an important support and assistance for the sustainable development of the logistics industry, providing practical support and improvement for enterprise operations, and achieving significant "efficiency enhancement" effects.

# 5. Conclusions

This article first analyzed the efficiency of 48 logistics enterprises using the BCC model and Malmquist index. The study found that the static operational efficiency was at a moderate level, and after 2017, the widespread application of digital technology further promoted the improvement of dynamic operational efficiency. Subsequently, through quantitative measurement of the development level of digital technology in logistics enterprises, it was found that there is a close relationship between the development level of digital technology and the operational efficiency of enterprises. Especially in the high level of digital technology development group, enterprises perform better in both static and dynamic operational efficiency. In summary, it can be concluded that digital technology has significantly improved the operational efficiency of logistics enterprises, especially in the current era of rapid digital development. Therefore, logistics companies should pay more attention to and utilize digital technology to enhance efficiency.

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