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Assessing Operational Efficiency and Technological Progress: An In-depth Study of China's E-payment Concept Listed Companies Using DEA-Malmquist Index

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

Electronic payment (e-payment) enterprises are third-party e-commerce platforms that provide services for buyers and sellers through network service platforms. This study evaluates the operational efficiency of 42 e-payment concept listed companies in Shanghai and Shenzhen stock markets from 2014 to 2019, using the data envelopment analysis (DEA)-Malmquist index model. The research results show that the overall operational efficiency of e-payment concept listed

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companies is in a good state, but some companies are constrained by constant or decreasing returns to scale, and should improve their management ability, streamline their organization, integrate their internal resources, accelerate their structural adjustment, reduce their invalid input, and increase their output level. Moreover, e-payment related enterprises should increase their research and development investment, pay attention to technological innovation, and enhance their core competitiveness. Facing the ever-changing market and more and more competitors, enterprises should use time and opportunity as competitive resources, seize the initiative, and avoid being eliminated by the market. This study provides a comprehensive and objective evaluation of the operational efficiency of e-payment concept listed companies in China, and offers some suggestions for improving their performance and competitiveness in the e-payment industry.

Keywords: E-payment; DEA; malmquist index; operational efficiency; China.

1. INTRODUCTION

E-payment enterprises, also known as third-party e-payment platforms or third-party e-commerce enterprises, refer to those that provide services for both suppliers and demanders of products or services through network service platforms, according to specific transaction and service standards. The services can include but are not limited to: supply and demand information release and search, transaction establishment, payment, logistics [1]. With the advancement of science and technology and the popularization of mobile payment in China, traditional payment methods are gradually being replaced by e-payment, and the rise of the e-payment industry also drives the development of mobile terminals. The e-payment industry originated from the online banking business, and later developed into an independent industry due to its fast and convenient operation and low cost. Furthermore, because of the convenience of e-payment, it can be used to conduct transactions anytime and anywhere, which stimulates consumption to some extent. Consumers are no longer bound by traditional payment methods when paying, so the rise of e-payment promotes the growth of sales volume, and both online and offline lines move forward synchronously. China is accelerating into the era of e-payment.

There are numerous methods for evaluating the operational efficiency of listed companies in modern society, and each method has its own reasons and advantages [2]. Based on the research theories and experiences of domestic and foreign e-payment related industry enterprises' operational efficiency evaluation, this study adopted the DEA-Malmquist index model to evaluate the operational efficiency, and used the actual financial data of enterprises to construct the performance evaluation system and verify the results.

2. AN OVERVIEW OF THE EXISTING RESEARCH AND THE FORMULATION OF THE RESEARCH QUESTION

Business operational efficiency (BOE) is the ability of an organization to use its resources effectively and efficiently to achieve its goals and objectives [3]. BOE is an important indicator of organizational performance and competitiveness, especially in the context of dynamic and uncertain environments. BOE can be evaluated from different perspectives, such as inputs (e.g., [4], outputs (e.g. [5], processes (e.g., Kumar and Harms, [6]), and outcomes (e.g., Merrill and Laur, [7]). However, measuring and comparing BOE across different organizations or units can be challenging, as they may have different characteristics, objectives, and operating conditions. Therefore, a relative and flexible approach is needed to assess and benchmark BOE.

Data envelopment analysis (DEA) is a useful and versatile technique that can measure and compare the relative efficiency of multiple decision-making units (DMUs) that use multiple inputs to produce multiple outputs [8]. DEA has been widely applied in different sectors and industries, such as education (e.g., [9,10]), health care (e.g., [11]; [12]), banking (e.g., [13]; [14]), and manufacturing (e.g., [15]; [16]), to evaluate and benchmark the BOE of different organizations or units. The applications of DEA in different sectors and industries have shown that DEA can provide a useful and comprehensive tool to measure and compare the BOE of different organizations or units. DEA can also help to identify the best practice organizations and the sources and magnitude of inefficiency, and to provide improvement targets and directions for the inefficient ones. Moreover, DEA can help to examine the factors affecting the BOE, such as size (e.g., [17]), location (e.g., [18]), discipline mix (e.g.[19]), expenditure (e.g., [20]), quality (e.g., [21]), and innovation (e.g., [22]), and to explore the relationship between the BOE and the performance of the organizations or units.

In addition, DEA can incorporate various factors, such as quality (e.g., [23]), environment (e.g.,[24]), risk (e.g., [25]), and innovation (e.g., [26]), into the efficiency analysis, and provide improvement targets and directions for the inefficient DMUs. DEA can also help to capture and balance the trade-offs and interdependencies among the different factors and dimensions of BOE, and to provide more comprehensive and realistic measures of efficiency. For instance, DEA can account for the quality of the outputs by using quality-adjusted inputs or outputs [23], or by using a two-stage approach that evaluates the efficiency and quality separately [21]. DEA can also account for the environmental and social impacts of the DMUs by using undesirable inputs or outputs [27], or by using a network approach that considers the intermediate processes and stages [28]. However, these extensions and modifications also have some limitations and challenges, such as: (a) they may increase the complexity and difficulty of the DEA model formulation and solution; (b) they may require more data and information, which may not be available or reliable; (c) they may introduce some subjective or arbitrary assumptions or specifications, which may affect the validity and applicability of the DEA model; and (d) they may not account for all the factors and uncertainties that affect the BOE, and may overlook some important aspects or interactions [29, 30].

On the other hand, DEA also faces some limitations and challenges, such as the lack of a universal and consistent definition and measurement of BOE; the difficulty of capturing and balancing the trade-offs and interdependencies among the different factors and dimensions of BOE; the scarcity of empirical and longitudinal studies to validate and generalize the findings and implications of BOE evaluation; and the dynamism and uncertainty of the internal and external environment [31,32], which require constant adaptation and innovation of BOE evaluation. Therefore, future research on BOE evaluation using DEA method should address these challenges and explore new perspectives and methods to enhance the validity and reliability of BOE evaluation, and to provide more practical and actionable insights and recommendations for the organizations.

How well do China's e-payment concept listed companies perform? The purpose of this study was to identify the problem of low output-input ratio of these companies, eliminate potential operational risks, and promote the high-quality development of e-payment related industry enterprises. For e-payment related industry enterprises, in the process of production and operation activities, in order to pursue profit maximization, it is helpful to study their BOE for the following reasons: (a) to stimulate the potential of the company and continuously improve the economic benefits; (b) to understand the causes of industry differences and improve the management level; (c) to provide reference for investors to make investment decisions. This study was the first to apply the DEA-Malmquist index model to evaluate the BOE of e-payment concept listed companies in China, and to analyze the factors affecting their efficiency changes.

3. METHODS

3.1 Selection of Input and Output Indicators

Operational efficiency of enterprises refers to the work behavior, mode, results and their objective impact of enterprises within a certain period of time. It can be defined as the work behavior and measurable work results that enterprises can describe in a specific time frame, as well as the quality and ability of enterprises in the past work. It is the measurement and feedback of the excellence of enterprises in completing tasks, the degree of achieving goals and the efficiency of achieving them under certain environmental conditions. Therefore, the selection of operational efficiency evaluation indicators should be guided and improved according to these criteria, so as to estimate the total amount of the work results that the enterprise can achieve in a specific time in the future.

In the existing research, Ding et al. [33] used earnings per share, debt-to-asset ratio, current ratio, quick ratio, total asset turnover, inventory turnover, fixed asset turnover, accounts receivable turnover as input indicators, and operating profit margin, earnings per share, return on equity, return on total assets, operating growth rate, net profit growth rate, total asset growth rate, equity growth rate as output indicators. They used FCE, CCR, C2GS2 and other models to comprehensively evaluate the performance of real estate listed companies.

Guan and Lu [34] selected fixed assets, current assets, shareholders' equity, operating costs, and number of employees at the end of the year as input indicators, and debt-to-asset ratio, current ratio, return on net assets, total asset turnover, and net asset growth rate as output indicators. They used CCR model to evaluate the operational efficiency of equipment manufacturing listed companies. Ding et al. [35] selected the initial total assets and operating costs as input indicators, and operating income, asset turnover, and return on total assets as output indicators. They used CCR and BCC models to evaluate the performance of China's biotechnology listed enterprises. Referring to the above research, this study selects the initial total assets, operating costs, and sales expenses as input indicators, and operating income and net profit as output indicators. These indicators are chosen based on the characteristics of the e-payment industry and the availability of the data, and they can reflect the input-output performance of the e-payment concept listed companies from different perspectives.

3.2 Data

The input and output indicator data of all decision making units (DMUs) were obtained from the financial reports issued by the e-payment concept listed companies in Shanghai and Shenzhen stock markets and audited by independent firms. These financial reports are publicly available and reliable sources of information for evaluating the performance of the e-payment concept listed companies. According to the classification of Sina Finance, there were 43 e-payment concept listed companies in Shanghai and Shenzhen stock markets as of December 31, 2022, but one of them, Changcheng Information (stock code: 000748), was delisted on June 28, 2019 due to the merger or division of the company, so its indicator data were excluded. This company was involved in a major asset restructuring and was acquired by another company, which resulted in its delisting from the stock market. Therefore, the final sample consisted of 42 DMUs with input and output indicator data. The sample covered a wide range of e-payment related industries, such as IT services, computer equipment, terminal equipment, integrated circuits and computer. In order to avoid the impact of negative value indicator data on the evaluation results, this study also standardized the indicator data before calculating the operational efficiency of each DMU using DEA method. The standardization process was to transform the original indicator data into non-negative values between 0 and 1, which could eliminate the influence of different units and scales of the indicators, and make the indicator data comparable and consistent.

3.3 Model

Data envelopment analysis (DEA) is a non-parametric method for analyzing technical efficiency based on the relative comparison of the evaluated objects. It was first proposed by Charnes, Cooper and Rhodes [36], who named the first model of DEA as the CCR model. DEA has the advantages of wide application range and relatively simple principle, especially in the analysis of multiple input and output situations, so its application range has expanded rapidly, involving education, agriculture, environment, macroeconomics, finance and many other fields [8]. The CCR model assumes that the scale efficiency of production technology is constant, or that all evaluated DMUs are in the optimal production scale stage, that is, in the stage of constant returns to scale, even if the scale efficiency of production technology is variable. However, in actual production, many production units are not in the optimal scale of production, so the technical efficiency obtained by the CCR model contains the component of scale efficiency. Banker, Charnes and Cooper [37] proposed a DEA model to estimate scale efficiency, which was later called the BCC model in the literature. The BCC model is based on variable returns to scale, and the technical efficiency obtained excludes the influence of scale, so it is called "pure technical efficiency". According to the CCR and BCC models, scale efficiency can be obtained by the following formula:

Scale efficiency = comprehensive efficiency (θ_{CCR}) / pure technical efficiency (θ_{BCC}).

When the data of the evaluated DMU are panel data containing multiple time point observations, the changes of productivity, technical efficiency and technical progress can be analyzed separately for the role of productivity changes, which is the commonly used Malmquist total factor productivity index (MI) analysis [38]. The Malmquist productivity index analysis method is an extended application of the DEA method, which mainly reflects two aspects of changes: one is the change of technical efficiency of the evaluated DMU in two periods (EC), and the other is the change of production technology (TC), which reflects the change of production frontier in DEA analysis (i.e. MI=EC×TC) [39].

4. RESULTS

4.1 DEA Efficiency

The operational efficiency scores and rankings of the 42 DMUs calculated based on the input-oriented CCR and BCC models are shown in Table 1. It can be seen that the evaluation scores and rankings of the CCR and BCC models are basically consistent, so the following analysis is mainly based on the CCR model. According to the CCR model, among the 42 companies, 11 achieved DEA efficient (θ_{CCR} = 1); 13 did not achieve DEA efficient, but scored higher than the average score; 18 scored lower than the average score, indicating that these companies have problems such as input redundancy or output deficiency in their operations, which will affect the long-term healthy and stable development of the enterprise if they are not discovered and corrected in time. Among them, ST Tiancheng (θ_{CCR} = 0.613) and Datang Telecom (θ_{CCR} = 0.614) had the lowest scores, indicating that these two companies have the largest room for improvement in operational efficiency.

According to the Shenwan industry classification, these 42 e-payment concept listed companies belong to different industries such as IT services, computer equipment, terminal equipment, integrated circuits (IC) and computers. As shown in Table 1, the communication supporting service industry achieved the overall DEA efficient of the industry (θ_{CCR} = 1) ; the overall operational efficiency of industries such as passive components (θ_{CCR} = 0.979) and IT services (θ_{CCR} = 0.907) was high; while the overall operational efficiency of the computer (θ_{CCR} = 0.777) and IC (θ_{CCR} = 0.819) industries was the lowest, indicating that these two industries have a large space for efficiency improvement, and enterprise managers need to constantly strengthen learning and improve operational efficiency according to their own characteristics.

In order to further explore the reasons for not achieving DEA efficient, this study conducted a projection analysis. Taking Datang Telecom (θ_{CCR} = 0.614), which has the lowest score in the IC industry, as an example, the company's three input indicators (initial total assets, operating costs and sales expenses) need to be reduced by 3.966 billion, 2.106 billion and 0.098 billion respectively to achieve DEA efficient, and the company is currently in the stage of decreasing returns to scale (RTS). This shows that the company needs to adjust its own business plan in the next strategic planning, and appropriately reduce the scale to improve the company's operational efficiency. It is not that the more input, the larger the scale of the enterprise, the better the operational efficiency. On the contrary, the more initial total assets the enterprise has, the more the enterprise should use these resources reasonably, and only the appropriate input can achieve DEA efficient. Therefore, when making decisions, company managers must fully analyze the output-input ratio, and when the output value remains unchanged, to achieve DEA efficient, they need to use resources reasonably and strive to reduce the input of input indicators. The projection analysis can help the e-payment concept listed companies to identify their inefficiency sources and to formulate effective improvement strategies.

4.2 Malmquist Index

The analysis results based on the input-oriented variable returns to scale Malmquist index model show that the overall total factor efficiency (MI) of the 42 companies has increased in the period of 2014-2019, indicating that the overall development trend of China's e-payment concept listed companies is good. In the years of 2014-2019, the number of companies that achieved MI improvement were 16, 20, 12, 19 and 23 respectively. In 2014-2015, the efficiency change index (EC) of the 42 companies increased by 5% on average, but due to the decrease of the technical progress index (TC) by 9%, MI decreased by 5%; in 2015-2016, MI increased by 3% on average due to the increase of TC by 15%, so even though EC decreased by 10%, MI still increased; in 2016-2017, MI decreased by 6%, EC did not change, but TC decreased by 6%; in 2017-2018, due to the decrease of TC by 9%, even though EC increased by 14%, MI only increased by 2%; in 2018-2019, EC only decreased by 1%, while TC increased by 13%, making MI increase by 11%.

Table 2 shows the EC, TC and MI indices of the 42 DMUs, and Fig. 1 illustrates the trend of EC, TC and MI of each industry during 2014-2019. It can be seen that the MI of the computer equipment industry showed a relatively stable trend in the period of 2014-2019, MI slightly decreased in 2014-2017, increased in 2018, but decreased again in 2019. EC changed significantly in 2014-2019, especially in 2015-2018, EC increased significantly. TC did not change much. The MI of the terminal equipment

Table 1. Operational efficiency scores based on input-oriented DEA model

No.	DMU	Industry	RTS	Benchmark (DMU No.)	θ_{BCC}	θ_{CCR}	SE [1]	Rank [2]
1	Xin Ya Da	IT service	Constant	1	1	1	1	1
2	Landun Shares	IT service	Constant	2	1	1	1	1
3	Aerospace Information	IT service	Decreasing	1; 16; 30	1	0.993	0.993	12
4	Xinkai Pu	IT service	Decreasing	1; 10; 37	0.932	0.923	0.990	16
5	Yilianzhong	IT service	Decreasing	1; 2; 10; 32	0.898	0.893	0.994	19
6	Jieshun Technology	IT service	Decreasing	1; 10; 37	0.915	0.841	0.919	28
7	Zhejiang Dahua	IT service	Decreasing	1; 16; 30	0.894	0.813	0.909	31
8	Hailian Jinhui	IT service	Decreasing	2; 16	0.887	0.794	0.895	33
	Mean				0.941	0.907		
9	Bohai Chemical	Computer equipment	Constant	9	1	1	1	1
10	Zhaori Technology	Computer equipment	Constant	10	1	1	1	1
11	Newland	Computer equipment	Decreasing	1; 2; 16	1	0.889	0.889	21
12	Guangdian Express	Computer equipment	Decreasing	1; 37	1	0.784	0.784	34
13	Xinguodu	Computer equipment	Decreasing	1; 2; 16	0.834	0.754	0.904	36
14	Yuyin Shares	Computer equipment	Decreasing	1; 2; 10; 32	0.715	0.710	0.993	38
15	Zhengtong Electronics	Computer equipment	Decreasing	1; 2; 16	0.683	0.680	0.996	39
	Mean				0.890	0.831		
16	Shensanda A	Terminal equipment	Constant	16	1	1	1	1
17	Tianyu Information	Terminal equipment	Decreasing	1; 9; 30	0.916	0.915	0.999	18
18	Dongxin Heping	Terminal equipment	Decreasing	1; 9; 30	0.887	0.878	0.990	24
19	Gaohong Shares	Terminal equipment	Decreasing	16; 30; 36	0.921	0.874	0.949	25
20	Hengbao Shares	Terminal equipment	Decreasing	1; 9; 16; 30	1	0.863	0.863	26
21	*ST Shangpu	Terminal equipment	Increasing	9; 16; 36	0.865	0.859	0.993	27
	Mean				0.932	0.898		
22	Tongfu Microelectronics	IC	Constant	22	1	1	1	1
23	Changdian Technology	IC	Decreasing	16; 22; 36	1	0.920	0.920	17
24	Unisoc	IC	Decreasing	1; 2; 16	0.973	0.887	0.912	22
25	National Technology	IC	Increasing	1; 2; 10; 32	0.676	0.674	0.997	40
26	Datang Telecom	IC	Decreasing	1; 2; 16	0.705	0.614	0.871	41
	Mean				0.871	0.819		
27	Nantian Information	Computer	Decreasing	1; 30; 33	0.844	0.835	0.989	30
28	Dahua Intelligent	Computer	Decreasing	2; 16	0.813	0.781	0.961	35

No.	DMU	Industry	RTS	Benchmark (DMU No.)	θ_{BCC}	θ_{CCR}	SE [1]	Rank [2]
29	Weishi Tong	Computer	Decreasing	1; 2; 32	0.807	0.715	0.886	37
	Mean				0.821	0.777		
30	Xiamen Xinda	Passive components	Constant	30	1	1	1	1
31	Shunluo Electronics	Passive components	Decreasing	2; 9; 16	1	0.957	0.957	15
	Mean				1	0.979		
32	*ST Xintong	Communication support service	Constant	32	1	1	1	1
33	Xingwang Ruijie	Communication support service	Constant	33	1	1	1	1
	Mean				1	1		
34	Jiaodian Technology	Internet information service	Decreasing	10; 32	0.989	0.963	0.974	14
35	Shengyibao	Internet information service	Decreasing	1; 9; 10	0.816	0.795	0.974	32
	Mean				0.903	0.879		
36	Kangqiang Electronics	Others	Constant	36	1	1	1	1
37	Meiya Pico	Others	Constant	37	1	1	1	1
38	China Coast Guar	Others	Decreasing	2; 9; 16	1	0.985	0.985	13
39	Quantong Education	Others	Increasing	1; 2; 9; 16	0.895	0.892	0.997	20
40	Tengbang International	Others	Decreasing	16; 22	0.887	0.880	0.992	23
41	Donggang Shares	Others	Decreasing	1; 30; 33	1	0.839	0.839	29
42	ST Tiancheng	Others	Increasing	1; 2; 10; 32	0.614	0.613	0.998	42
	Mean				0.914	0.887		

Note: 1. SE (Scale efficiency) = θ_{CCR} / θ_{BCC}; 2. Ranking based on CCR model score.

Table 2. Efficiency change (EC), technological change (TC) and Malmquist index (MI) during 2014-2019

DMU	Industry	EC					TC					MI				
		14-15	15-16	16-17	17-18	18-19	14-15	15-16	16-17	17-18	18-19	14-15	15-16	16-17	17-18	18-19
Xin Ya Da	IT service	1	1	0.624	1.604	1	0.916	1.029	0.988	0.684	1.049	0.916	1.029	0.616	1.097	1.049
Landun Shares	IT service	0.702	1.425	1	1	1	0.717	1.279	1.024	1.024	0.904	0.503	1.822	1.024	1.024	0.904
Aerospace Information	IT service	1	1	1	1	1										
Xinkai Pu	IT service	1.005	0.930	1.059	1.079	0.978	0.806	1.072	0.987	0.899	1.053	0.810	0.997	1.044	0.970	1.030
Yilianzhong	IT service	1.347	0.700	0.939	1.500	1.022	0.725	1.185	0.976	0.730	1.022	0.977	0.829	0.916	1.095	1.045
Jieshun Technology	IT service	1.111	1	0.995	0.751	1.083	0.995	0.881	0.977	0.957	1.016	1.106	0.881	0.972	0.719	1.101
Zhejiang Dahua	IT service	1.049	0.896	0.916	1.206	0.982	0.968	1.092	1.002	0.891	1.019	1.016	0.978	0.918	1.075	1.001
Hailian Jinhui	IT service	1.190	0.701	1.275	0.989	0.952	0.925	1.289	0.975	0.981	1	1.101	0.903	1.243	0.971	0.952
Mean		1.051	0.957	0.976	1.141	1.002	0.865	1.118	0.990	0.881	1.009	0.918	1.063	0.962	0.993	1.012
Bohai Chemical	Computer equipment	1	1	1	1	1	1.026	1.18	0.922	1.902	0.557	1.026	1.18	0.922	1.902	0.557
Zhaori Technology	Computer equipment	1	1	1	1	1	1.094	0.791	0.901	1.001	0.962	1.094	0.791	0.901	1.001	0.962
Newland	Computer equipment	1	1	1	0.952	1.050	1.028	1.090	1.063	0.955	0.986	1.028	1.09	1.063	0.91	1.036
Guangdian Express	Computer equipment	1	1	1	1	1	1.196	0.803	1.102	0.731	1.017	1.196	0.803	1.102	0.731	1.017
Xinguodu	Computer equipment	1.079	0.927	0.738	1.668	1.061	0.876	1.093	0.946	0.769	1.012	0.946	1.014	0.698	1.283	1.074
Yuyin Shares	Computer equipment	0.942	0.713	0.957	1.423	1.335	0.897	1.259	1.002	0.747	1.120	0.845	0.898	0.959	1.063	1.495
Zhengtong Electronics	Computer equipment	1.153	0.575	1.075	1.497	1.131	0.794	1.577	0.9	0.621	0.984	0.915	0.908	0.967	0.929	1.113
Mean		1.025	0.888	0.967	1.220	1.082	0.987	1.113	0.977	0.961	0.948	1.007	0.955	0.945	1.117	1.036
Shensanda A	Terminal equipment	1.051	1.096	1	0.868	1.054	0.918	1.971	0.685	0.583	1.033	0.966	2.159	0.685	0.506	1.089
Tianyu Information	Terminal equipment	1.312	0.911	0.935	1.207	0.832	0.867	1.144	1.063	0.916	1.034	1.138	1.042	0.994	1.105	0.860

DMU	Industry	EC					TC					MI				
		14-15	15-16	16-17	17-18	18-19	14-15	15-16	16-17	17-18	18-19	14-15	15-16	16-17	17-18	18-19
Dongxin Heping	Terminal equipment	1.228	0.919	0.91	1.024	0.83	0.868	1.089	0.95	0.932	1.042	1.066	1.001	0.865	0.955	0.865
Gaohong Shares	Terminal equipment	1.019	0.884	0.994	1.059	1.004	0.984	1.146	0.981	0.938	1	1.002	1.013	0.975	0.993	1.004
Hengbao Shares	Terminal equipment	1	0.785	1.114	1.014	0.874	1.125	0.814	0.896	0.963	1.045	1.125	0.639	0.998	0.976	0.914
*ST Shangpu	Terminal equipment	1.042	0.456	1.559	1.297	1.134	0.886	1.638	0.958	0.714	0.942	0.923	0.747	1.494	0.927	1.068
Mean		1.109	0.842	1.085	1.078	0.955	0.941	1.300	0.922	0.841	1.016	1.037	1.100	1.002	0.910	0.967
Tongfu Microelectronics	IC	1	1	1	1	1	0.751	1.102	1.004	0.881	1.009	0.751	1.102	1.004	0.881	1.009
Changdian Technology	IC	1	1	1	1	1	0.993	1.022	1.028	0.977	1.009	0.993	1.022	1.028	0.977	1.009
Unisoc	IC	1	1	0.852	1.031	1.082	0.878	0.897	0.868	0.997	1.016	0.878	0.897	0.74	1.028	1.099
National Technology	IC	1.201	0.907	0.798	1.628	0.86	0.782	1.108	0.918	0.676	0.957	0.94	1.005	0.733	1.101	0.823
Datang Telecom	IC	0.920	0.778	1.396	1.284	0.687	1.015	1.081	0.955	0.998	1.150	0.934	0.84	1.333	1.281	0.790
Mean		1.024	0.937	1.009	1.189	0.926	0.884	1.042	0.955	0.906	1.028	0.899	0.973	0.968	1.054	0.946
Nantian Information	Computer	1.215	0.819	0.919	1.362	1.018	0.894	1.221	1.079	0.786	0.996	1.087	1	0.991	1.070	1.014
Dahua Intelligent	Computer	1.038	0.791	1.098	1.12	0.955	0.911	1.423	0.899	0.794	1.008	0.946	1.126	0.987	0.889	0.963
Weishi Tong	Computer	1.114	0.797	0.934	1.191	1.003	0.897	1.172	0.954	0.769	1	0.999	0.935	0.891	0.916	1.003
Mean		1.122	0.802	0.984	1.224	0.992	0.901	1.272	0.977	0.783	1.001	1.011	1.020	0.956	0.958	0.993
Xiamen Xinda	Passive components	1	1	1	1	1										
Shunluo Electronics	Passive components	1.069	1	1	1	0.965	0.979	1.205	0.802	1.336	1.01	1.047	1.205	0.802	1.336	0.975
Mean		1.035	1	1	1	0.983	0.979	1.205	0.802	1.336	1.010	1.047	1.205	0.802	1.336	0.975
*ST Xintong	Communication support service	1.104	0.900	0.892	1.245	1	0.853	1.291	0.937	0.81	5.673	0.942	1.162	0.836	1.009	5.673
Xingwang Ruijie	Communication	1	1	1	1	1	1.025	1.034	1.014	0.984	1.051	1.025	1.034	1.014	0.984	1.051

DMU	Industry	EC					TC					MI				
		14-15	**15-16**	**16-17**	**17-18**	**18-19**	**14-15**	**15-16**	**16-17**	**17-18**	**18-19**	**14-15**	**15-16**	**16-17**	**17-18**	**18-19**
	support service															
Mean		1.052	0.950	0.946	1.123	1	0.939	1.163	0.976	0.897	3.362	0.984	1.098	0.925	0.997	3.362
Jiaodian Technology	Internet information service	1.138	0.887	0.716	1.573	1	0.946	0.821	0.94	0.925	1.292	1.077	0.729	0.674	1.455	1.292
Shengyibao	Internet information service	1	0.648	1.065	1.02	0.891	0.642	0.891	0.915	0.941	1.036	0.642	0.578	0.975	0.959	0.924
Mean		1.069	0.768	0.891	1.297	0.946	0.794	0.856	0.928	0.933	1.164	0.860	0.654	0.825	1.207	1.108
Kangqiang Electronics	Others	1	0.826	1.211	1	1	0.857	1.454	0.833	1.065	0.971	0.857	1.201	1.009	1.065	0.971
Meiya Pico	Others	1	1	1	1	1	0.953	1.052	1.084	0.941	1.011	0.953	1.052	1.084	0.941	1.011
China Coast Guar	Others	0.981	1.124	1	1	1	0.918	1.671	0.64	1.053	1.115	0.9	1.878	0.64	1.053	1.115
Quantong Education	Others	1	0.705	1.033	1.278	0.932	0.7	0.977	0.803	0.751	0.995	0.7	0.689	0.829	0.96	0.927
Tengbang International	Others	1	0.953	1.05	0.898	0.855	0.877	1.041	0.874	0.909	1.004	0.877	0.992	0.917	0.816	0.859
Donggang Shares	Others	1.043	1.092	1	1	0.902	1.013	0.872	0.952	1.066	1.147	1.057	0.952	0.952	1.066	1.035
ST Tiancheng	Others	1.13	0.798	1.052	1.117	0.912	0.745	1.318	0.93	0.766	1.007	0.842	1.053	0.979	0.856	0.918
Mean		1.022	0.928	1.049	1.042	0.943	0.866	1.198	0.874	0.936	1.036	0.884	1.117	0.916	0.965	0.977

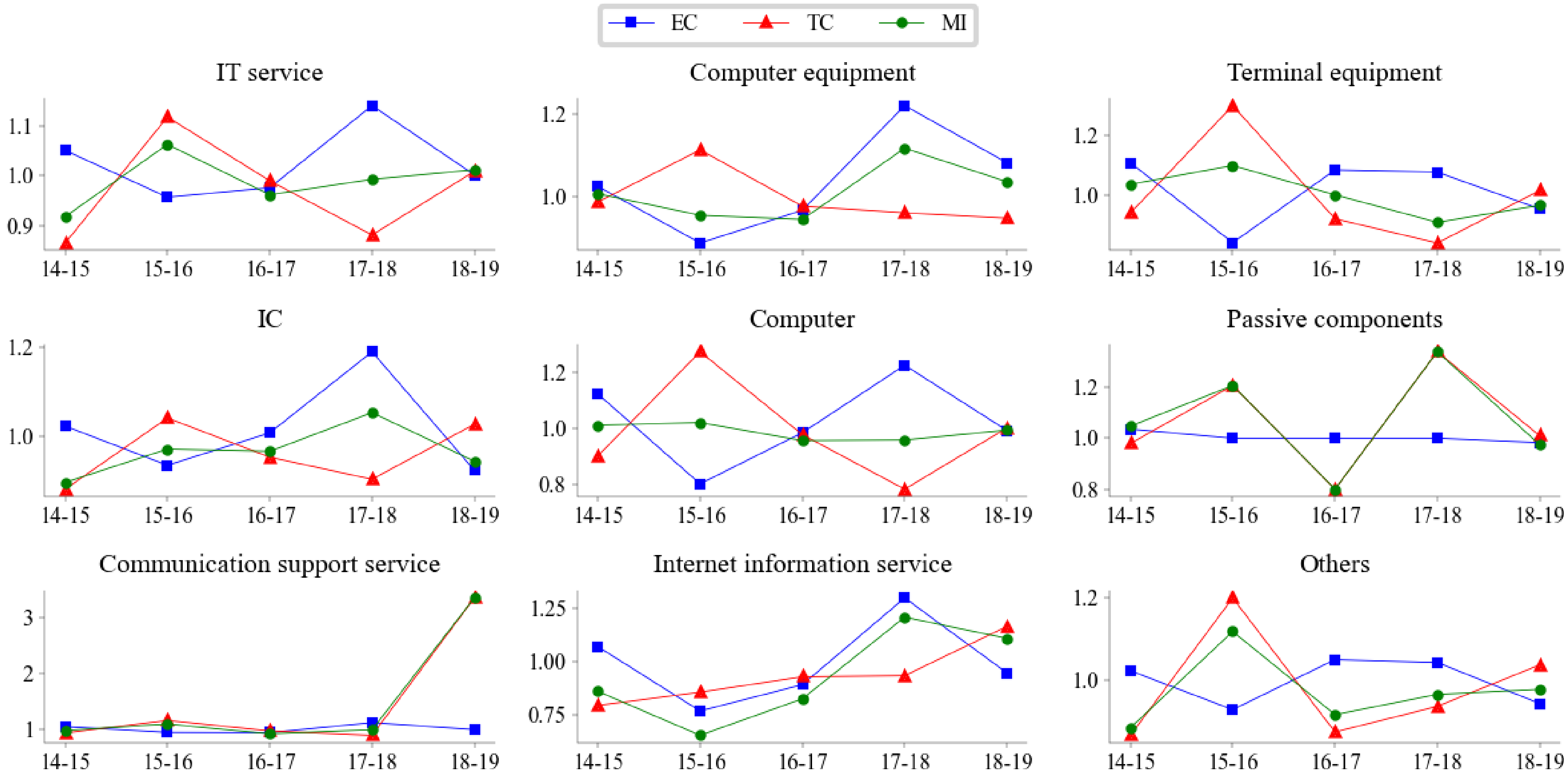

Fig. 1. The trend charts of EC, TC and MI by industry during 2014-2019

industry changed the most, and only this industry's MI was downward, from 1.04 to 0.97. In this industry, the six companies in these years, EC decreased significantly in 2016, but in the same year, TC increased significantly. In 2018, both EC and TC decreased significantly. Further analysis found that some enterprises in this industry, such as *ST Shangpu, have major problems in their operation, and if the enterprise managers do not adjust the input and output in time, the enterprise will not be able to develop in the long run. In terms of technology, except for the computer equipment industry, other industries have continuously improved their technical level in 2014-2019, so TC has been increasing. According to the survey, many enterprises, such as Landun Shares, have introduced advanced technologies many times in the development of the enterprise to improve their own technical level.

5. DISCUSSIONS AND CONCLUSION

This study evaluates the operational efficiency of 42 e-payment concept listed companies in the Shanghai and Shenzhen stock markets, and conducts a horizontal and vertical comparative analysis of the evaluation results. The results have reference significance for the listed e-payment related enterprises to improve their operational efficiency, and also provide some insights for many e-payment related enterprises that are eager to go public. Generally speaking, the operational efficiency of China's e-payment concept listed companies was in a good state in 2014-2019, which was inseparable from the fierce competition in the domestic e-payment related industry. The open and competitive environment gave China's e-payment related industry a strong vitality and competitiveness. However, the research also found that constant or decreasing returns to scale were also a constraint factor for some DMUs to improve their operational efficiency, so these companies should avoid relying solely on expanding the scale to improve their performance. For example, although Datang Telecom had a large operating scale, the decreasing returns to scale prevented it from exerting the advantages of economies of scale. For such enterprises, they should improve their management ability, streamline their institutions appropriately, integrate their internal resources, speed up the pace of structural adjustment, strive to reduce ineffective input, and vigorously improve the output level.

As a rapidly developing industry in China, e-payment related enterprises should increase their R&D investment and pay attention to technological innovation. With the change of the market, the competition of e-payment related enterprises will be a contest of comprehensive competitiveness, rather than a contest of single project operation. Therefore, enterprises should pay attention to technological innovation and improve their core competitiveness. Core competitiveness, as a valuable resource of enterprises, is an important factor that can make enterprises develop continuously in the long term. It is an organic combination of different technologies and management abilities. Therefore, enterprises should pay attention to technological innovation, create an effective and healthy management environment, and continuously improve their operational efficiency. Facing the ever-changing market and more and more competitors, enterprises can only seize the opportunity and take the initiative in the market by taking time and opportunity as the resources of competition, and avoid being eliminated by the market.

In this study, we first introduce the DEA-Malmquist index model and the data sources, then we present the analysis results of the operational efficiency and the productivity changes of the e-payment concept listed companies, and finally we discuss the implications and limitations of our research. This study is the first to apply the DEA-Malmquist index model to evaluate the operational efficiency of e-payment concept listed companies in China, and to analyze the factors affecting their efficiency changes. This study provides a comprehensive and objective evaluation of the operational efficiency of e-payment concept listed companies in China, and offers some suggestions for improving their performance and competitiveness in the e-payment industry. The main findings and contributions of this study are summarized as follows:

First, the overall operational efficiency of e-payment concept listed companies in China improved in the period of 2014-2019, which indicates that the e-payment industry has a good development potential and prospects in China. However, there were still significant differences in the operational efficiency among different companies and industries, which suggested that there was still room for improvement and optimization for some companies and industries.

Second, the main factor affecting the operational efficiency of e-payment concept listed companies in China was the TC index, which reflected the change of production technology and innovation ability. The technical progress index increased in most years, except for 2014-2015 and 2017-2018, which indicated that the e-payment industry had been constantly innovating and upgrading its technology and products, and had maintained a strong competitiveness in the market. However, the technical progress index also showed some fluctuations and declines in some years, which indicated that the e-payment industry also faced some challenges and risks, such as the rapid changes of market demand, the fierce competition of new entrants, the strict regulation of government policies, and the protection of user privacy and security.

Third, the EC index, which reflected the change of technical efficiency and management ability, decreased in most years, except for 2014-2015 and 2017-2018, which indicated that the e-payment concept listed companies in China had not fully utilized their input resources and had not achieved the optimal output level. The efficiency change index also showed that some companies and industries were in the stage of decreasing returns to scale, which meant that they had over-expanded their scale and had not achieved the optimal scale efficiency. Therefore, the e-payment concept listed companies in China needed to improve their management ability, streamline their organization, integrate their internal resources, accelerate their structural adjustment, reduce their invalid input, and increase their output level.

The limitation is the study was conducted based on the established CCR and BCC model. Future research should consider applying advanced techniques and methods, such as artificial intelligence [40], machine learning [40, 41], big data analytics and network data envelopment analysis [42], to improve the data quality and availability, to enhance the model accuracy and robustness, and to generate more insights and solutions for operational efficiency evaluation and improvement.

In conclusion, this study showed that the e-payment concept listed companies in China had improved their operational efficiency and technological progress in the period of 2014-2019, but they also faced some challenges and risks, such as the scale efficiency, the market demand, the competition, the regulation, and the security. Therefore, the e-payment concept listed companies in China needed to improve their management ability, streamline their organization, integrate their internal resources, accelerate their structural adjustment, reduce their invalid input, increase their output level, increase their R&D investment, pay attention to technological innovation, and enhance their core competitiveness.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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