Application of Data Envelopment Analysis Method Based on E-commerce Internet Supply Chain Management

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Objectives: The department mainly studies the application of data envelopment analysis method based on e-commerce Internet supply chain management in China's economic management. Methods: Taking the number of state-owned shares of the listed company and the size of the company as external environmental factors, firstly, the three-stage data packet analysis (DEA) is used to measure the operational efficiency of 312 e-commerce companies, thus a DEA model is established. Results:Secondly, the DEA projection analysis is used to quantify the output of the inefficient company, and the improvement plan of the company's factor input is proposed according to the size of the projection value. Conclusion: Finally, the sample is selected for empirical analysis. The results show that projection analysis can effectively improve the economic operation efficiency of enterprises.

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Enterprise efficiency has always been one of the most popular topics in economics. Efficient enterprises can get more output with less input and gain more market share with excess profit, while inefficient enterprises resources, reducing market competitiveness and gradually losing their share because of redundant input or insufficient output [1]. Are state-owned enterprises and state-owned economies highly efficient or inefficient? For a long time, there are both "state-owned enterprise operational efficiency loss theory or low efficiency theory" and "state-owned enterprise high efficiency theory", and others support "state-owned enterprise efficiency paradox" and "enterprise efficiency no difference theory" [2]. At the same time as the efficiency debate, the state-owned enterprises share reform is also in progress. The state-owned enterprises with single ownership are changed into multiple-ownership by the reform of shareholding system, in order to improve the overall productivity of state-owned enterprises [3]. Theref ore, based on the theoretical research and the actual needs of China's economic development, China has begun to actively develop the capital market to optimize the ownership structure of state-owned enterprises and raise development funds [4]. At the end of 2013, there are 2 515 A-share listed companies, of which about 41.84% are state-owned companies, 68.35% are owned by central and local state-owned enterprises, and the capital scale advantage is obvious [5]. However, from the perspective of the annual market capitalization of the central and local state-owned listed enterprises in 2013, the annual market capitalization of both companies is negative, especially the central listed companies' market capitalization drop as high as 8.98%. Obviously, the e-commerce companies with the advantages of capital scale have not achieved the optimal efficiency under the support of capital to promote market value growth. This is a question that needs to be studied [6].

The research on the efficiency of state-owned enterprises is more concentrated in the generalized output efficiency and allocation efficiency abroad[7]. As far as input-output efficiency is concerned, western researchers often use production function to study the output efficiency of enterprises by calculating their contribution to economic growth. Buchanan thinks that Pareto efficiency examines the allocation of production resources, organizational forms and distribution of consumer goods [8]. Meanwhile, the domestic evaluation methods of state-owned enterprise efficiency are familiar to researchers with the innovative application of various analysis methods [9]. At present, it can be found through combing that the domestic methods for measuring the operational efficiency of enterprises mainly include: financial index analysis method, parameter analysis method and non-parametric analysis method [10]. Through combing the existing research literature, it is found that there are a large number of research results on the efficiency of state-owned enterprises at home and abroad, but no systematic and holistic research has been formed [11]. In many studies, due to the different actual conditions, the conclusions of different studies are different. The disputes over the efficiency of state-owned enterprises have arisen, and different evaluation models have also made the comparison of research results less objective and convincing [12]. In addition, it can be found that the efficiency optimization of state-owned enterprises with low operational efficiency is not widely concerned, and the quantitative analysis of efficiency optimization is lacking. Based on the above analysis, it is considered that the future research on the operational efficiency of state-owned enterprises should be improved from the following aspects[13]. Firstly, based on the previous qualitative research, more and more methods are used to measure efficiency, such as data envelopment analysis, stochastic frontier analysis and grey relational analysis. Select the three-stage DEA model including nested SFA analysis to calculate the operational efficiency of e-commerce companies [14]. Secondly, the state-owned enterprises with relatively low operational efficiency should improve their operational efficiency and how much to achieve effective state is also one of the contents to be studied [15].

METHODS

DEA Model

DEA model is based on the input and output of the decision-making unit to determine whether it is located on the "production frontier", that is, from the input of the smallest, maximum output of the Pareto optimal solution set, and then judge the relative effectiveness of the decision-making unit. Since the data envelopment analysis (DEA) method is proposed, some scholars have formed the first DEA model C2R on the basis of Farrell model with the assumption that scale returns remain unchanged. Some scholars have proposed BC2 model on the assumption that scale returns are changeable. C2R is used to judge whether the technology is effective and the scale is effective at the same time, while BC2 is only used to judge whether the technology is effective or not. The combination of the two can obtain the decomposition formula of the overall efficiency to the technical efficiency and the scale efficiency. The DEA model has already formed a more mature research system, so there is no detailed explanation. The basic steps of the three stage DEA method are: The first phase only considers inputs and outputs, obtains the efficiency value of DMU and the difference of input or output. In the second stage, the difference of income in the first stage is taken as dependent variable, and the relationship between dependent variable and environment variable and random item is analyzed by SFA to obtain new input value. The third stage needs to calculate the DMU efficiency again. The selection is to calculate the operation efficiency of e-commerce companies by referring to the above methods. The specific steps are as follows: The first stage: import the data into BC2 model to get the initial operating efficiency of each e-commerce company. However, since the DEA model does not consider the environmental variables and random errors, the initial values can't reflect what factors are affected. In the second stage, the SFA regression analysis is used to analyze the input relaxation variables in the first stage. The regression model is:

$$S_{ni} = f^n(z_i;\beta^n) + v_{ni} + u_{ni,} n = 1,2,\ldots,N; i = 1,2,\ldots,I; u_{ni} \geq 0 \quad (1)$$

Among them, S_{ni} is input relaxation variable value, z_i is environment variable, β^n represents the parameter to be estimated, and $f^n(z_i;\beta^n)=z_i\beta^n$ is usually used. $v_{ni}+u_{ni}$ represents the error term, where v_{ni} obeys normal distribution and represents random interference term, v_{ni} represents invalid management. Using the estimated parameters obtained by SFA regression analysis, the input of DMU elements in each investment decision-making unit is adjusted. The adjustment formula is as follows:

$$x_{ni}^{*}=x_{ni}-z_i\widehat{\beta}^n \quad (2)$$

Among them, x_{ni}^{*} is the adjusted input and x_{ni} is the original input. The third stage: using the adjusted input and initial output, the DEA model is imported to recalculate the operational efficiency of the DMU. Considering that input is easier to control than output, an input-oriented BC2 model is used to calculate the operational efficiency of e-commerce companies.

Sample Selection and Data Sources

By the end of 2017, there are 1 076 A-shares listed on the Shanghai Stock Exchange, but the main research object is E-commerce companies in A-shares on the Shanghai Stock Exchange. Therefore, 588 samples of listed companies are selected according to the two indicators ®of "controlling human type" and "operating nature". According to the industry classification guidelines of listed companies of China Securities Regulatory Commission, the situation of the 588 e-commerce companies after the industry clustering is shown in the Figure It can be seen that all industries are distributed, so it is representative.

Figure 1
Industrial Distribution of State-Owned Listed Companies

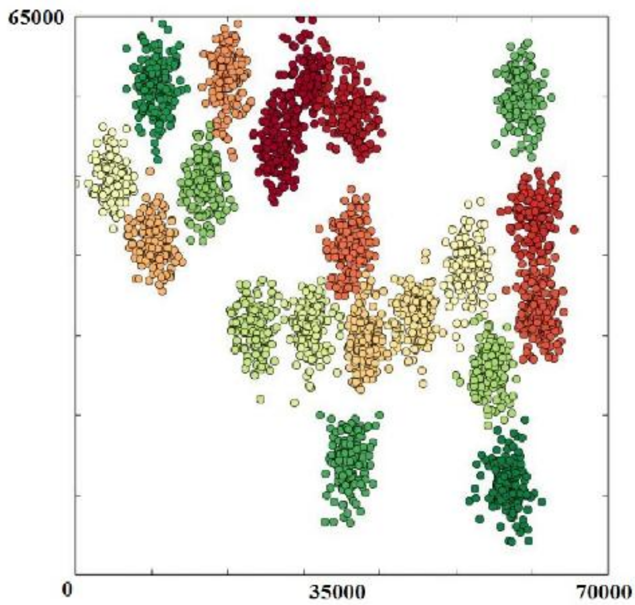
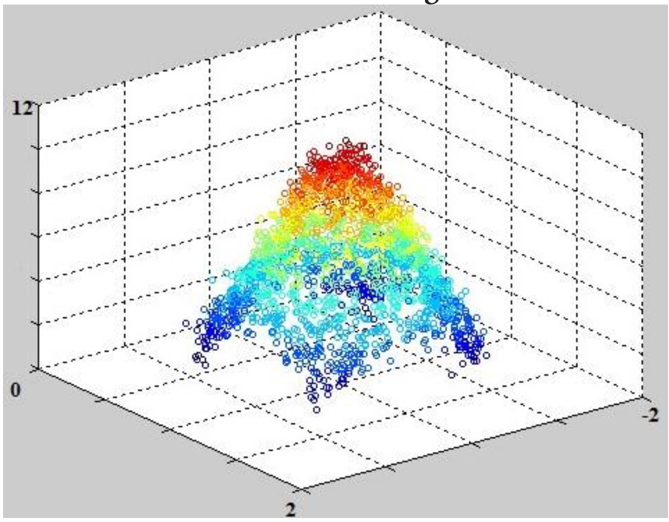


Figure 2
Data Clustering



Considering that the main purpose is to use the three-stage DEA model to study and calculate the operational efficiency of e-commerce companies. in order to ensure that the final conclusions have the corresponding accuracy and persuasion, the sample selection should be as representative as possible. In addition, when selecting samples, it is necessary to consider the large gap between the regulatory and influencing factors between different industries. If the number of company samples in an industry is too small, it is not suitable for research. Therefore, the listed companies of e-commerce-related business are selected, in addition to the 25 listed companies warned of risks and the four listed companies listed in the IPO in 2017, and finally determine the sample range of 400 e-commerce companies. After determining the sample range, based on the consideration of the research purposes, the study period of the listed company's operating efficiency is limited to 2017, and the selected samples are listed by the IPO before 2017, the data is up to December 31, 2017. This choice is mainly considered in 2017 is the last year after the latest IPO suspension in China's securities market reopened, and the reorganization of state-owned enterprises after the reopening of the IPO in 2013, a number of large e-commerce compa nies reorganized. In order to reduce the impact of IPO or M&A on the operational efficiency of selected samples, 2017 is selected as the sample year. All data are from wind database, giant tide Information Network and the annual report of listed companies. Company operation will inevitably require continuous investment in order to maintain normal and orderly business development. In terms of measuring the annual investment in the company's working capital, it is mainly measured by operating costs and period expenses. Operating cost refers to the main operating cost and other operating costs. Period expenses mainly include sales expenses, management expenses and financial expenses. Operating costs and period expenses largely reflect the capital elements invested by the company in conducting business and maintaining operations, and therefore can be selected as indicators of capital investment. Compared with previous studies, the period cost is regarded as an indicator, not three indicators, which can optimize the structure of input indicators, but also achieve the practical purpose of investment indicators.

The three stage DEA model is closer to the actual situation after eliminating the influence than the traditional DEA. Therefore, according to the specific operation of e-commerce companies and the actual external impact of the company, the following two external environmental factors are selected: firstly, the number of state-owned shares. The relationship between ownership structure and corporate efficiency has been a hot topic in the research field of modern companies. State-owned shares are owned by the state and most of the senior executives of e-commerce companies are appointed by administrative means. The government may have too much intervention in the company's operations due to political goals. The problem of “agent entrustment” may also make the senior executives of listed companies insufficiently motivated, thus causing the ineffectiveness of the listed company's governance mechanism to be detrimental to the company's operational efficiency. Therefore, it is assumed that the number of state-owned shares negatively affects the operating efficiency of listed companies. Secondly, size of company. According to the theory of enterprise life cycle, with the enlargement of the company scale, the operating efficiency of the company may show a trend of "first long and then decline". The sample size of e-commerce companies is different. In order to eliminate the impact of company size on efficiency evaluation results, it is feasible to take the size of the company as an exogenous environmental factor. When using DEA to deal with efficiency problems, the model requires that all operational data must be non-negative, and some of the selected samples of e-commerce companies in 2017, there are individual losses. After the sample is re-screened, the correlation between input and output indicators is tested by E-Views 6.0 software, as shown in Table 1 below.

Table 1
Correlation Analysis of input output indexes

	Earnings per share (EPS)	Business income	Total Pre-tax Profits
Operating cost	0.048688186	0.997619895	0.914193048
Cost of the period	0.077161190	0.953912309	0.971767343
Total remuneration	0.080125105	0.881543763	0.929952324

It can be seen from Table 1 that the correlation coefficient between the operating cost, the period expense and the total compensation of the input index and the operating income and total profit and tax of the output index are all above 0.88. It can be seen that the correlation between the input index and the operating income and total profit and tax is very high. However, the correlation coefficients between the input index and the output index EPS are only 0.048688186, 0.077161190 and 0.080125105, respectively. Judging from the correlation coefficient, the linear correlation between each input index and earnings per share (EPS) is not high, but considering that EPS is the most commonly used financial index to measure the profitability of listed companies, reflecting the company's profitability comprehensively, it can still be used as one of the output indicators. After comprehensive consideration, it can be seen that the selected index system is relatively reasonable.

RESULTS

In order to more specifically explain the operational efficiency of the sample listed companies, the descriptive statistics of each efficiency index are as follows, as shown in Table 2 below.

Table 2
Descriptive Statistics of Sample Initial Operating Efficiency of State Owned Listed Companies

	Integrated operational efficiency TE	Pure technology operation efficiency PTE	Scale efficiency SE
minimum value	0.224	0.373	0.481
mean value	0.642	0.679	0.946
standard deviation	0.157	0.159	0.067
Effective DMU number	9	10	4
DMU number greater than 0.8	55	72	303
DMU number greater than 0.5 less than 0.8	202	203	8
DMU number greater than 0.5	55	37	1

Figure 3
SVM Support Vector Machine Method 1

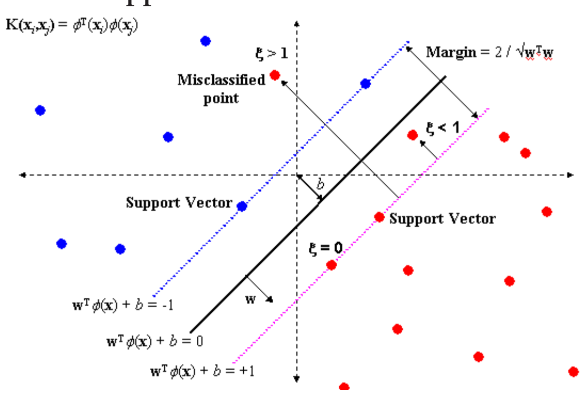
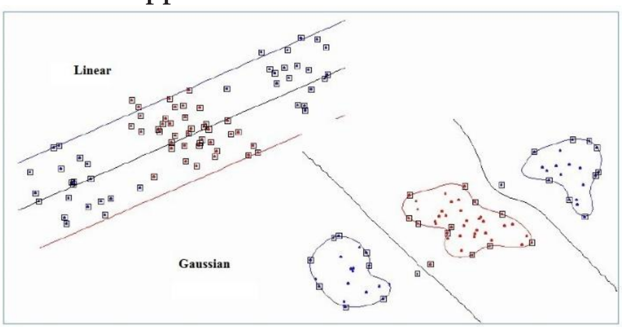


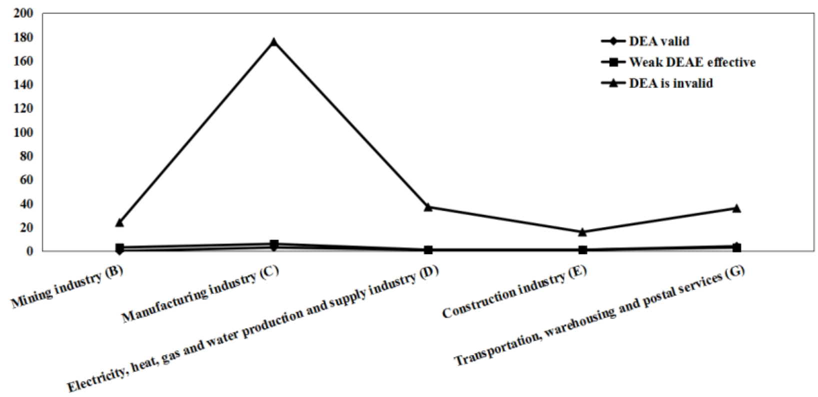
Figure 4
SVM Support Vector Machine Method 2



Data are processed by SVM support vector machine algorithm, as shown in figures 3 and 4. From the descriptive statistics in table 2, the average value of the overall operating efficiency, pure technical operation efficiency and scale efficiency of e-commerce companies in the sample is 0.642, 0.679 and 0.946 respectively. The difference from the optimal efficiency value is 0.358, 0.321 and 0.054, which means that the sample company still has room to improve on these three efficiency indicators.

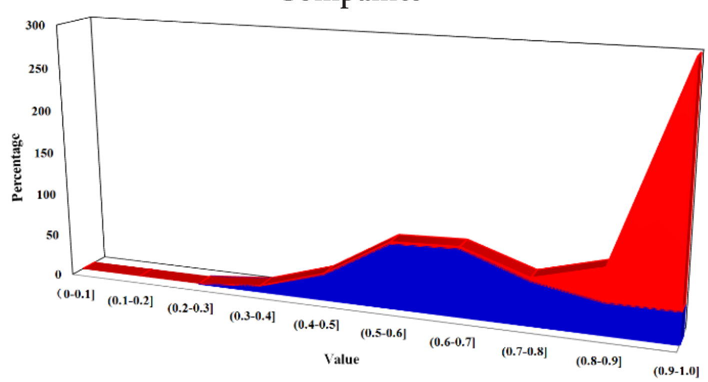
From the industry distribution, a total of three manufacturing sample companies, one power, thermal, gas and water production and supply industry sample companies, one construction companies and four transport, warehousing and postal companies to achieve DEA effective; Three mining companies, six manufacturing companies, one electric, thermal, gas and water production and supply company, one construction company and three transportation, storage and postal companies have reached weak DEA efficiency. The remaining mining (24, manufacturing (176), electricity, heat, gas and water production and supply (37), construction (16) and transportation, warehousing and postal (36) are in a state of DEA inefficiency. As shown in Figure 5 below.

Figure 5
Sample DEA Efficiency State, Industry Distribution Quantity of State Owned Listed Companies



The DEA model can measure the scale reward level of DMU according to the input-output index, as shown in Figure 6. In the sample, the number of e-commerce companies with increasing returns to scale is129, the number of e-commerce companies with decreasing returns to scale is 169, while the number of companies with constant returns to scale is only 14. This means that in the "inverted U" curve of scale returns, most e-commerce companies are on the left and right sides of the optimal scale returns, and can promote the growth of scale returns by expanding or reducing the scale. Pure technical operation efficiency and scale efficiency will lead to weak EA validity as long as one side is in the effective state. If both are in the invalid state, DMU will be in DEA validity, that is to say, one of PTE and SE is equal to 1DMU weak DEA validity. Neither of them is equal to 1DEA validity. Then according to the results, there are 10 sample companies whose PTE equals 1, and 4 sample companies whose SE equals 1, which can judge that only 14 e-commerce companies are in weak DEA valid state. According to the distribution of efficiency value, 37 companies with PTE value less than 0.5, accounting for 11.86% of the total sample; 72 companies with PTE value greater than 0.8, accounting for 23.08% of the total sample; the remaining 203 companies (65.06%) had PTE values between 0.5 and 0.8, with the largest number of companies between 0.5-0.6 and 0.6-0.7. There are only 1 companies with a scale efficiency se value of less than 0.5 and only 8 of the sample companies with a total of 0.32%, SE values between 0.5 and 0.8, while the majority of the sample companies have an SE value of more than 0.8 and a total of 303, which accounts for 97.16%, as shown in Figure 5 below. The above analysis shows that the inefficiency of comprehensive operation of most of the sample listed companies with ineffective DEA is caused by pure technical operation efficiency, and management or technical factors have an impact.

Figure 6
Distribution of PTE and SE Values for Initial Operation of State Owned Listed Companies



From the perspective of scale return, more than 40% of the 312 samples in 2017 are in a state of increasing returns to scale, more than half of the companies are in a decreasing state, and only 14 are in the same scale. There are two explanations for increasing returns to scale. One is the efficient use of input of resource factors, and the other is that the production scale is insufficient to make full use of production efficiency. E-commerce companies in increasing returns to scale sample companies continue to invest in factors of production can get higher returns, while the decline in the state of the company needs to reduce investment.

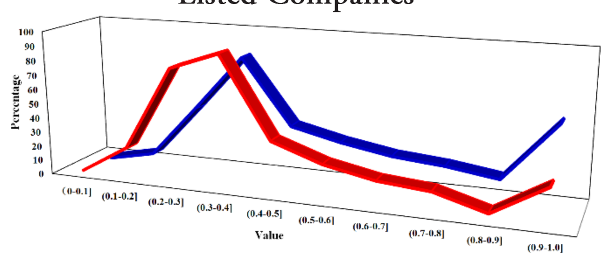
From the average efficiency, the overall operating efficiency of 312 e-commerce companies in 2017 is 0.431, and the distance from the efficiency frontier is 0.569, which means that the operating efficiency loss of the sample companies is more and more serious, as high as nearly 60%. After adjusting the input, the pure technical efficiency and scale efficiency are only 0.549 and 0.809, respectively. The influence factor of pure technical efficiency on comprehensive operational efficiency has reached 0.451, while the influence factor of scale efficiency is only 0.191. Therefore, pure technical efficiency is still the main reason for the low comprehensive operational efficiency. In order to be able to more directly grasp the operation efficiency of the 312 companies, a brief descriptive analysis is made first.

Table 3
Descriptive Statistics of the Third Stage Operational Efficiency of the State-Owned Listed Companies

	Integrated operational efficiency TE	Pure technology operation effect PTE	Scale efficiency SE
minimum value	0.095	0.141	0.253
mean value	0.431	0.549	0.809
standard deviation	0.227	0.262	0.193
Effective DMU number	22	41	23

From the interval distribution of efficiency values, TE values are mostly between 0.2-0.3 and 0.3-0.4, and as high as 170 companies are in this interval, which means that about 55% of the sample companies are between 60% and 80% of the efficiency loss. And from the distribution map, most companies have a TE (crste) value of less than 0.6. In addition, it can be seen in Figure 7 that TE and PTE values have the same trend of interval distribution, showing inefficient interval distribution. It is proved again that the main factor of inefficient comprehensive operation is the efficiency loss of pure technical efficiency.

Figure 7
Distribution of TE and PTE Value of Third Stage Operation Efficiency of State Owned Listed Companies



In terms of industry distribution of efficiency value, two of the sample companies belonging to mining industry are in DEA effective state, five are in weak DEA effective state, and the remaining 20 are in DEA invalid state. Of the sample companies belonging to manufacturing industry, 6 are in DEA valid state, 7 are in weak DEA valid state, and the remaining 172 are in DEA invalid state. In the power, thermal, gas and water production and supply industries, 4 companies are in DEA efficiency, 4 companies are in weak DEA efficiency and 31 companies are in DEA inefficiency. Only one company and 17 companies with weak DEA validity in construction industry are ineffective; 10 companies in transportation, warehousing and postal industry are in DEA validity, 3 weak DEA validity and 30 DEA validity. From the perspective of industry distribution, the manufacturing industry and construction industry companies are more inefficient, inefficient companies in the industry accounted for 94% of the larger proportion.

DISCUSSION

The efficiency of DEA model is based on the input and output variables of selected samples. It should be noted that the efficiency value obtained is only the relative efficiency value, not the absolute efficiency value, that is, the efficiency of DMU within the selected sample range can only be evaluated by DEA efficiency value. According to the characteristics of 312 e-commerce companies listed on the Shanghai Stock Exchange, from the perspective of the production of listed companies, the evaluation system of e-commerce company's operational efficiency is constructed. And in the empirical operation, the influence of external environmental factors is considered, which makes up for the deficiency of traditional DEA model which does not consider environmental variables and random errors in evaluating operational efficiency, and objectively and accurately gets the relative efficiency value of e-commerce companies. Using the three-stage DEA method, the comprehensive operational efficiency, pure technical efficiency and scale efficiency of 312 e-commerce companies in China are compared and analyzed. It is hoped that the operating efficiency level of 312 e-commerce companies can be measured in a fairer environment, excluding external factors, and the conclusions will be helpful to the reform of the operating efficiency of e-commerce companies.

Human Subjects Approval Statement

This paper did not include human subjects.

Conflict of Interest Disclosure Statement

None declared.

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