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Assessing the Operational Performance of the Transformation AI Industry in Taiwan - Critical Factors for the Transition

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Abstract This research that by estimating the companies of the technical efficiency (TE) and the results of the data mining methodology (DMM), explaining find company efficiency and the companies characteristics. First, we will apply a Data Envelopment Analysis (DEA) analysis model to assess Taiwan companies' operational efficiency. Then, we will use a big data model to identify critical factors for a sustainability transition. (1) In this study, we found that a total of four companies—Hon hai, Ares, Yulon, and Micro-stra—successfully transformed steps (TE = 1). (2) According to the results of the above DMM model. Thus, were the companies able to make good on the promise of AI. We demonstrated the need for more AI talent to transform their steps and increase RD spending successfully. Due to reduced labor costs, the EFA was reduced, and NBR and EPS increased significantly after the transition. So, these critical factors will help the enterprise to transfer its AI industry operation type successfully. Further, we discover that AI can be applicable to save employment and increase its short-term profit.

Keywords: *data envelopment analysis, artificial intelligence, operating efficiency, data mining methodology*

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1. Introduction

We know that the high-tech industries are the lifelines of Taiwan economics; among them, information electronics is the leading character. Taiwan, based upon electronic manufacturing, is facing the enormous challenges from labor-intensive countries and the problems of factories perpetually moving abroad. Yet, creativity, the remaining advantage, makes us feel not too pessimistic about the future of Taiwan. With the technological innovation's nature of ever-renewing, ever-changing and ever-improving proficiency, Taiwan can introduce itself and manifest globally its irreplaceable techniques. In this constant changing era, Taiwan electronics industry can no longer depend upon labor intensity and capital intensity; only by innovation and refinement can an industry find its own way and then thrive.

Over the past forty years, Taiwan has successfully and rapidly transformed its previously agriculture-dominated economy into a sophisticated global manufacturing powerhouse. By 2017, the Gross National Product in Taiwan is expected to be 4501863.12 TWD Million by the end of this quarter, according to Trading Economics global macro models and analyst’s expectations. Looking forward, the analyst’s point the estimate Gross National Product in Taiwan to stand at 4501853.66 in 12 months’ time. In the long-term, the Taiwan Gross National Product is projected to trend around 4501853.66 TWD Million in 2020, according to the Trading economics company of the econometric models. More importantly, the rapid economic development was accomplished with relatively stable prices and very low unemployment. Since the economy took off in the 1960s, the inflation rate has been kept below 5 percent and the unemployment rate under 3 percent for most of the time.

However, we knew most Taiwanese companies still repeatedly believe that the "OEM" industry is the only way we can make money. Taiwan's excellent manufacturing capability is commendable, but Taiwan’s computer-generation industry is the cause of changes in the past two years. As the power of computer consumption has subsided in the past two years, major brands have adopted the easiest way - contending with low spending power, launching lower-priced models, and seizing emerging markets such as India and China. Thus, Taiwanese companies are also facing the challenge of industrial restructuring. Under the wave of the fourth wave of the industrial revolution, if the speed of transition does not keep pace with the world's rhythm, it can only meet the fate of being marginalized in the global economy. Hence, Taiwan’s computer-generation industry is a need transformation step.

Artificial Intelligence (AI), also known as machine intelligence, refers to a machine made by man out of the demonstrated wisdom. Usually, artificial intelligence refers to the human intelligence technology that is realized by ordinary computer programs. The term also points out the scientific field of research on whether such a smart system can be implemented and how it is implemented. At the same time, the human population has begun to converge. The Poole, Mackworth, and Goebel [1] point that the definition of the general teaching material is "intelligent agent research and design". The wisdom subject refers to a system that can observe the surrounding environment and take actions to achieve the goal. Thus, the McCarthy [2] point out that AI is highly technical and professional, and each branch is in-depth and unrelated, and thus involves a wide range of areas. Besides, Shein [3] noted the importance of AI talent. Thus, the paper point that regardless of whether a company is in a sector where the disruptive potential is lower and adoption is likely to be slower. It follows from what has been said that no sector or business is in any way immune from the impact of AI. Therefore, we see that AI will be the development trend of enterprises in the future.

Moreover, we seen that AI has been researched in recent years has increased noticeably. Thus, AI has made great progress in the application of a large number of key technologies and breakthroughs in machine operation, among which the most popular applications are uncrewed vehicles, AI medical, AI finance, and AI agriculture; in other words, the AI will undoubtedly be an important key to the next wave of wisdom revolutions. At this stage, in Taiwan, the government has launched the "Taiwan AI Action Plan (2018-2021)" with the vision of "Innovative experience first, secondly hard and soft development together, and stimulating the greatest kinetic energy in the industry". The plan is hoped that the Taiwan companies will gain opportunities and advantages in the next wave of smart revolutions. Moreover, the Taiwanese companies create the economy the miracle of growth and continue to play in the world's economic influence and business sustainability opportunity.

However, a similar problem in Taiwan companies take AI transformation opportunity is not yet widely addressed in the literature published domestically. Relevant theoretical foundations are likewise not widely. The study's purpose was to explore whether every company is suitable for the transformation steps. Furthermore, it is also a well-established fact that the management of performance and productivity helps increase organizational competitiveness and adds to the country's economic growth. First, we will apply the DEA model to analyze Taiwanese-related AI companies' operational efficiency in this study. The results are then compared to the results of pre- the transformation steps. Besides, we use the big data model to find critical factors for the sustainability transition.

The paper comprises five main sections: Section 1 introduces the research background and goal of this research. Section 2 reviews the Conceptual framework and the overview of the policy. Section 3 introduces our methodology. Section 4 presents the empirical results. And, finally, the last section provides the concluding remarks.

2. Literature Reviews

Schendel and Patton [4] presented a question." Why are some firms able to break-out of stagnating or declining performance pattern?" Therefore, they were regarded as the first that considered the cause of the turnaround situation in assessing the appropriateness of turnaround strategies. Furthermore, the topic is considered largely idiosyncratic and open-end. It seems compatible with some researchers view turnaround as a performance issue in strategic management; some researchers view turnaround as a process in organizational management. The research strategies also vary from one context to another. As stated by the researchers have asked managers for their perceptions of decline and recovery, gleaned insights from secondary data and used database [5].

A majority of think that defining turnarounds on the basis of profitability alone is problematic [6]. For example, profitability may decline very slowly at first and then suddenly plummet and there may be a time lag between improvements in competitiveness and subsequent profit improvement. Moreover, a gradual loss of competitiveness is often not reflected as a gradual deterioration in profitability. Thus, the Pandit [6] point that in situations where the crisis facing the firm is not severe, small changes such as cost pruning can affect recovery. However, when the crisis facing the firm is more severe, more dramatic changes such as asset reduction or market reorientation are required. The Zeng et al., [7] point out that the" Uncertainty in the Global Economy: Great Concerns Should Be Given". By reason of Many uncertainties exist in the development of the world economy. For example, the American economy is still in potential danger and the dollar has fluctuated quite a lot lately; the high prices of an oil strike the economies of many countries; the debates over RBM exchange rate regime are still hot; trade protectionism comes back again. All those factors influence the future world economy; therefore, great concerns and analysis should be given accordingly.

Also, in managing change, the debate has raged for some time as to whether the industry is best served by continuous improvement or radical business transformation [8]. From research, theoretical, and case-based, the general conclusions would seem that both forms of change are relevant [10]. Examples of the former include Virgin Atlantic and General Electric (GE) Capital who continually innovate their services to keep ahead in their market. Examples of the latter include CISCO and Microsoft Corporation, who reinvented computing/networking in the 1990s, displacing such incumbents as IBM, Hewlett Packard Enterprise (HPE), and Digital Equipment Company. Lessons from radical transformation include the fact that it leads companies into areas where the company has much to learn; the risk of continuous improvement is that it does not challenge companies to learn quickly enough [12].

On the other hand, if from the point of organizational management, the suggests that turnaround is simply recovery to profitability from a loss situation, and it turnaround situation as one where a company suffers declining economic performance for an extended period of time and the performance level is so low that the survival of the company is in threat unless efforts are made to improve its performance [13]. Thus, when the problems arise primarily from inefficiency, retrenchment is warranted. However, when problems are strategic, the turnaround effort should focus on entrepreneurial moves to reposition the business. Obviously, the industry needs to business transformation exhibit a high degree of correlation with repositioning in the marketing [14].

Hence, Uncertainty in the Global Economy can have a significant impact on Taiwanese companies or industries. According to Taiwan's government flats pointed out that domestic, mostly the manufacturer of the original equipment, panel, and part-transmission industries and other industries are facing a structural transformation, and there may have a survival crisis. The global economic recovery causes the material and labor costs to boost the price to a historical height, increasing the production cost of the Original Equipment Manufacturer (OEM) or Original Design Manufacturer (ODM) manufacturing industry. In simple terms, this production cost includes manufacturing and labor costs; thus, the OEM and ODM manufacturing industry lower profit year-on-year. At this stage, the OEM and ODM manufacturing industry needs to business transformation. [15].

In recent years, big data related technologies developed greatly and rapidly, which provides new ideas and tools for smart management and decision-making [16]. Zeyu et al. [17] thought that the data mining is widely applied in the model study for simulation of complex systems and decision-making support. Big data recorded almost all the activities of systems which leads to a possibility of system modeling, predicting and optimizing. Thus, the big data application or data mining methodology can help to extract the value of data and thus better decisions can be made, and the high costs of the runtime, which would make the problem intractable, can be avoided. However, the Stacey et al., [18] point there are a number of techniques used in data mining, but not all of them can be applied to all types of data. Neural network algorithms, for example, can be used to quantify data (numerical data), but they cannot qualify data precisely (categorical data). For that the reason, one single technique cannot be used to perform a complete data mining study and each technique has its own scope of applications. For example, Neural networks can analyze imprecise, incomplete, and complex information and find important relationships or patterns from this information; by their special ability to "learn". Usually, the patterns involved in this kind of analysis are so complicated that they are not easily detected by humans or by other types of computer-based analysis. Additionally, the same is true of the data mining techniques have been applied to analyze and their corresponding causes in the efficiencies.

When in the economic downturn. Evaluating the operational efficiency of companies have gathered importance in recent years. Thus, in recent years, many scholars have employed DEA to analyze the operational efficiency and examine whether the widespread utilization of assessments can effectively enhance growth efficiency in order to improve operations management. According to the statistics, DEA has been applied empirically to more than one thousand cases in fields as diverse as transportation, educational administration, law, forest management, medicine, banking, military maintenance, and administration [19]. However, in evaluating the operational performance of companies, a distinct characteristic of DEA is the concept of relative efficiency and the simultaneous examination of different units' inputs and outputs. The efficiency value of a decision-making unit (DMU) is calculated by using the linear programming method; the efficiency value of a DMU is between 0 and 1, wherein 1 indicates an efficient unit and a value of less than 1 indicates an inefficient unit. Accordingly, a functional formula between the input and output is unnecessary, since the use of a method setting production function produces non-parametric errors that can be avoided. Furthermore, most scholars generally use DEA model in operational efficiency studies. The Technical Efficiency (TE) results obtained by the traditional Charnes-Cooper-Rhodes (CCR) model [21], which contains inherent disadvantages due to the influence of random factors. Moreover, the relative efficiency value does not denote absolute efficiency, and not to find critical factors for the sustainability transition. We, therefore, recommend the use of the big data model and this difficulty can be readily solved by applying the big data model technique.

As mentioned above, when the problems arise primarily from inefficiency, retrenchment is warranted. However, when problems are strategic, the turnaround effort should focus on entrepreneurial moves to reposition the business. The industry needs to business transformation exhibit a high degree of correlation with marketing repositioning. However, there have been limited related research published domestically or overseas and scanty theoretical discourses on topics such as whether the company that introduces the business sustainability opportunity can capitalize on such initiatives to enhance operational efficiency and increase its competitiveness. Thus, this research adopts the quantitative research method and uses the DEA analysis method to measure the company's competitiveness and use the big data to find critical factors for the sustainability transition.

3. Methodology

Little has been known about the conceptual framework and working methods of transformation steps at present in Taiwan. Therefore, this study employed quantitative results to analysis study approach (DEA model and big data model) to gain an in-depth and holistic understanding of the efficiency of company management and suggests that to find out the factors and future trends of common transformation.

Hence, the analysis consists of a two-step procedure. To begin with, we estimate the company's efficiency scores through DEA model. Finally, this study uses the DMM model such as CRISP-DM to explore the most important factor for companies' characteristics related to companies' management efficiencies.

3.1. DEA Model

The DEA model, proposed by Charnes et al. [21] and known as CCR, assumes the DMUs to be assessed operate within a technology where efficient production is characterized by constant returns to scale (CRS). As above is obtained from the following Equation (1):

$$\mathrm{Max}h_k = \frac{\sum_{r=1}^{s} u_r y_{rk}}{\sum_{i=1}^{m} v_i x_{ik}} \quad (1)$$

$$s.t \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1 \quad , \quad j = 1,\ldots,n$$

$$u_r, v_i \ge \varepsilon > 0, \quad r = 1,\ldots\ldots,s, \quad i = 1,\ldots\ldots,m$$

Where x_{ij} is the amount of the i-th input to DMU j, y_{rj} is the amount of the r-th output to DMU j; u_r , v_i are called r virtual multiplier output and i virtual input multiplier; The value of h_k obtained is termed the relative efficiency and is called the CCR efficiency, the ε is a non-Archimedean positive element smaller any real number (10^{-6}), the CCR model is called non-Archimedean small number.

Banker et al. [22] modified this basic model to permit the assessment of the productive efficiency of DMUs where efficient production is characids by variable returns to scale (VRS). The VRS model, known as BCC, differs from the basic CCR model only in that in includes in the previous formulation the convexity constraint:

$$\sum_{i=1}^{n} \lambda_j = 1 \quad (2)$$

In summary, the following equation can be obtained for computing efficiencies:

Technical Efficiency (TE) = Pure Technical Efficiency (PTE) × Scale Efficiency (SC)

3.2. Data Mining Methodology--The Generic CRISP-DM Reference Model

We to find critical factors for the sustainability transition and this study adopts Cross Industry Standard Process for Data Mining (CRISP-DM) method as the analytical process. CRISP-DM Methodology was proposed by DaimlerChrysler, SPSS, NCR in 1996. On the other hand, it can be known from the literature that the CRISP-DM methodology to investigate a wide variety of scientific questions, and to have some meaningful information extracted. So, this study adopts the CRISP-DM method as the analytical process to explore the most important characteristics related to efficiencies of school management. As shown in Figure 1, the CRISP-DM reference model for data mining provides an overview of the life cycle of a data mining project. It contains the phases and/or procedures of a project, their respective tasks, and their related inputs and outputs.

Berry and Linoff [23] pointed the life cycle of a data mining project is broken down in six. The sequence of the phases is not strict. In Figure 1, the arrows indicate only the most important and frequent dependencies between phases, but in a particular project, it depends on the outcome of each phase which phase, or which particular task of a phase, has to be performed next. Data mining is not finished once a solution is deployed. The lessons learned during the process and from the deployed solution can trigger new, often more focused business questions. Subsequent data mining processes will benefit from the experiences of previous ones. In the following, we outline each phase and/or procedures briefly in Figure 1.

1) Business Understanding

This initial phase focuses on understanding the project objectives and requirements from a business perspective, and then converting this knowledge into a data mining problem definition, and a preliminary project plan designed to achieve the objectives.

2) Data Understanding

The data understanding phase starts with an initial data collection and proceeds with activities in order to get familiar with the data, to identify data quality problems, to discover first insights into the data, or to detect interesting subsets to form hypotheses for hidden information.

3) Data Preparation

The data preparation phase covers all activities to construct the final dataset (data that will be fed into the modeling tool(s)) from the initial raw data.

4) Modeling

In this phase, various modeling techniques are selected and applied, and their parameters are calibrated to optimal values.

5) Evaluation

At this stage in the project, you have built one or more models that appear to have high quality, from a data analysis perspective. Before proceeding to final deployment of the model, it is important to more thoroughly evaluate the model, and review the steps executed to construct the model, to be certain it properly achieves the business objectives.

6) Deployment

Creation of the model is generally not the end of the project. Usually, the knowledge gained will need to be organized and presented in a way that the customer can use it.

As mentioned above, this research adopts the quantitative research method and uses DEA analysis method to measure the competitiveness of the company and use the big data to find critical factors for the sustainability transition.

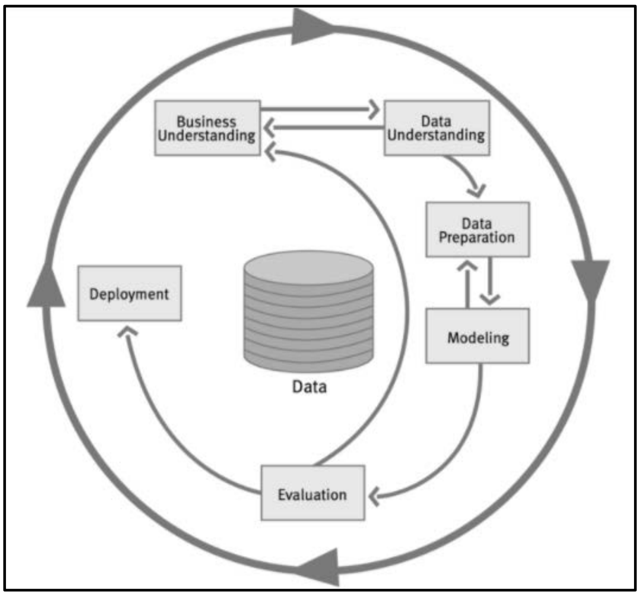

Figure 1. Six phases of CRISP-DM

4. Empirical Results and Analysis

The empirical analysis of this study is mainly comprised of three main sections. Section 1 describes the study objects in this study. Section 2 presents the data description and correlation analysis between inputs and outputs. Section 3 analyzes the efficiency analysis of the DEA model. Finally, Section 4 discusses the results for CRISP-DM methodology and to find critical factors.

4.1. Study Objects and Variable for Inputs and Outputs in This Study

The study objects in this study are described as follows: This study aimed to analyze if the working methods of transformation steps increase the company's operational efficiency. In this investigation, our data comes from most of Taiwan's industry analysis thinks the 10 companies are forward-looking and specialized in the AI industry. The study spanned five years and included periods before and after the introduction of transformation steps and periods—the Data samples of the study in Table 1.

4.2. Variables Selection for Inputs and Outputs in This Study

We employ the institution functions of the firm in this paper, which is in line with the competitive AI industry in Taiwan. This can also effectively benefit a firm's operations and improve an AI firm's efficiency. In accordance with this approach, we specify three types of firm's output, namely the net business revenues (business revenues after tax), ratio of gross income before tax, ratio of net income after tax, ratio of business profit, turnover of accounts payable, and earnings per share. The first four types of output constitute the main activities of AI firms; with the last two representing an extended source of revenue for firms (Chiesa and Toletti, 2003). The input measures based on the above output entail operating resources. We select the following three input factors: number of staff employed, expense of fixed assets, and R & D expenses.

Next, we determine the relationships between inputs and outputs. The DEA model requires definitions of inputs and outputs so that when inputs are added, outputs will increase. We employ a correlation analysis to test for isotonicity (i.e., the positive direction of the relationship between inputs and outputs). According to the results of the inter-correlation analysis, it is clear that the correlation coefficients between our chosen outputs and inputs are all positive. Third, we have further utilized correlation analysis to determine the appropriate inputs/outputs in accordance with this approach [24]. The less correlation between inputs and outputs is neglected since it is weak production oriented. Thus, we specify two types of firm output, namely net business revenues (NBR) and earnings per share (EPS). Three types of input, namely number of staff employed (NSE), expense of fixed assets (EFA), and R & D expenses (RD) are included. As discussed above, in this paper, the final correlation analysis is displayed in Table 2 and the input-output variables definitions of listed in Table 3.

Furthermore, the official report from the Commission on National Corporations of the Ministry of Economic Affairs provides a rich source of data on the operations of all of Taiwan's AI firms. We have gathered the requisite data for 10 companies in Taiwan, covering the period 2013 to 2017. Please note that we chose the time span of 2013 to 2017 because the Taiwanese government has included the AI industry in the ten emerging important industries and we evaluated the promotion performance in the first five-year periods.

4.3. Efficiency Analysis

First, this study employs a DEA to evaluate the efficiency and effectiveness of the companies. Furthermore, the managerial decision-making matrix is addressed and suggestions made to help AI company managers improve performance.

Table 1. Data samples of the study

NO	Full name of companies	DMU
1	Hon Hai Precision Ind. Co., Ltd.	Hon-hai
2	Yulon Motor Co., Ltd.	Yulon
3	Delta Electronics, Inc.	Delta
4	Teco Electric & Machinery Co., Ltd.	Teco
5	Shihlin Electric & Engineering Corp.	Shihlin
6	Hiwin Technologies Corp.	Hiwin
7	Aares International Corp.	Ares
8	Airtac International Group	Airtac
9	Micro-star International Co., Ltd.	Micro-star
10	Advantech Co., Ltd.	Advantech

Source: This Study.

Table 2. Correlation test and analysis

	x_1	x_2	x_3	y_1	y_2
x_1	1	.969**	.995**	.980**	.311*
x_3		1	.965**	.983**	.311*
x_2			1	.982**	.308*
y_1				1	.301*
y_2					1

Source: This Study *Coefficients significant at 5%. ** Coefficients significant at 1%.

Table 3. DEA model input and output indicators definitions

NO	Indicators	Code	Definition
1	namely number of staff employed (NSE)	x_1	Input Indicator
2	expense of fixed assets (EFA)	x_2	Input Indicator
3	R & D expenses (RD)	x_3	Input Indicator
4	business revenues (NBR)	y_1	Output Indicator
5	earnings per share (EPS)	y_2	Output Indicator

Source: This Study.

4.3.1. Technical Efficiency (TE)

According to the result of DEA model that the TE value of companies during the period under study is 1 (TE=1), indicating that if no environmental factors are considered, these companies need not make any improvements or adjustments in terms of resource allocation, management decisions, and output scale. As shown in Table 4 and Table 5.

Table 4. Efficiency Values for 2013-2017 Under the DEA model

DMU	TE	PTE	SE	RTS
2013 Teco	0.485	0.485	1.000	Decreasing
2014 Teco	0.422	0.423	0.999	Increasing
2015 Teco	0.370	0.373	0.992	Decreasing
2016 Teco	0.457	0.467	0.980	Increasing
2017 Teco	0.451	0.461	0.979	Increasing
Average	***0.437***	***0.442***	***0.990***	
2013 Hon-hai	1.000	1.000	1.000	Constant
2014 Hon-hai	1.000	1.000	1.000	Constant
2015 Hon-hai	1.000	1.000	1.000	Constant
2016 Hon-hai	1.000	1.000	1.000	Constant
2017 Hon-hai	1.000	1.000	1.000	Constant
Average	***1.000***	***1.000***	***1.000***	
2013 Shihlin	0.849	0.852	0.997	Decreasing
2014 Shihlin	0.770	0.789	0.975	Decreasing
2015 Shihlin	0.819	0.857	0.955	Decreasing
2016 Shihlin	0.712	0.718	0.992	Increasing
2017 Shihlin	0.728	0.746	0.975	Increasing
Average	***0.775***	***0.792***	***0.979***	
2013 Delta	0.536	0.613	0.875	Decreasing
2014 Delta	0.504	0.634	0.796	Decreasing
2015 Delta	0.481	0.547	0.880	Decreasing
2016 Delta	0.432	0.497	0.868	Decreasing
2017 Delta	0.425	0.468	0.909	Decreasing
Average	***0.476***	***0.552***	***0.866***	
2013 MICRO-STAR	1.000	1.000	1.000	Constant
2014 MICRO-STAR	1.000	1.000	1.000	Constant
2015 MICRO-STAR	1.000	1.000	1.000	Constant
2016 MICRO-STAR	1.000	1.000	1.000	Constant
2017 MICRO-STAR	1.000	1.000	1.000	Constant
Average	***1.000***	***1.000***	***1.000***	

Source: This Study.

Table 5. Efficiency Values for 2013-2017 Under the DEA model

DMU	TE	PTE	SE	RTS
2013 Airtac	0.979	1.000	0.979	Decreasing
2014 Airtac	0.723	1.000	0.723	Decreasing
2015 Airtac	0.823	1.000	0.823	Decreasing
2016 Airtac	0.570	1.000	0.570	Decreasing
2017 Airtac	1.000	1.000	1.000	Constant
Average	***0.819***	***1.000***	***0.819***	
2013 Advantech	0.867	1.000	0.867	Decreasing
2014 Advantech	0.733	1.000	0.733	Decreasing
2015 Advantech	0.849	1.000	0.849	Decreasing
2016 Advantech	0.744	1.000	0.744	Decreasing
2017 Advantech	0.868	0.872	0.995	Increasing
Average	***0.812***	***0.974***	***0.838***	
2013 Yulon	1.000	1.000	1.000	Constant
2014 Yulon	1.000	1.000	1.000	Constant
2015 Yulon	1.000	1.000	1.000	Constant
2016 Yulon	1.000	1.000	1.000	Constant
2017 Yulon	1.000	1.000	1.000	Constant
Average	***1.000***	***1.000***	***1.000***	
2013 Ares	1.000	1.000	1.000	Constant
2014 Ares	1.000	1.000	1.000	Constant
2015 Ares	1.000	1.000	1.000	Constant
2016 Ares	1.000	1.000	1.000	Constant
2017 Ares	1.000	1.000	1.000	Constant
Average	***1.000***	***1.000***	***1.000***	
2013 Hiwin	0.909	0.933	0.974	Decreasing
2014 Hiwin	0.786	0.988	0.796	Decreasing
2015 Hiwin	0.713	0.820	0.869	Decreasing
2016 Hiwin	0.480	0.602	0.796	Decreasing
2017 Hiwin	0.800	0.808	0.990	Increasing
Average	***0.737***	***0.830***	***0.885***	

Source: This Study.

4.3.2. The Managerial Decision-Making Matrix

We according to Norman and Stoker (1991), the TE can be split into four main groupings as follows:

The robustly efficient units as follows: These will appear on many reference sets and are likely to remain efficient unless there are major shifts in their fortune. We found two companies have robustly efficient and described as follows: Hon-hai and Ares appearances in the reference sets, and the total efficiency value of companies during the period under study is 1 (TE=1).

The marginally efficient units as follows: These will appear on only one or two reference sets (including their own) and are likely to drop to below 1 if there was even a small drop in the value of an output variable or a small increase in the value of an input variable. We found two companies and described as follows: Yulon and Micro-stra. These companies need to make small improvements or adjustments in terms of resource allocation, management decisions, and output scale.

The marginally inefficient units as follows: These will have an efficiency rating in excess of, say, 0.9 (but less than 1) and could soon raise their score towards 1. The results showed that we found none of the company.

The distinctly inefficient units as follows: With an efficiency score of less than 0.9, these units would have difficulty in making themselves efficient in the short term. Besides, these companies need to major change in circumstances, in terms of resource allocation, management decisions, and output scale. The results showed that we found 6 companies and described as follows: Teco, Shihlin, Delta, Advantech, Hiwin, and Airtac.

4.4. Results of Data Mining Methodology

To solve the DEA model does not show its correlations, patterns, trends, or relationships to the problem. Therefore, to perform data mining methodology and attempt to find the company characteristics based on company efficiency factors. Section 1 describes the steps of the procedure of data mining methodology. Section 2 describes the major selected factors affecting company efficiency. Lastly, section 3 discusses the empirical results of applying data mining methodology to find the company characteristics.

4.4.1. Model Setups

This section describes data mining steps of CRISP-DM methodology and to find the company characteristics. Thus, this section describes "typical" sources and model settings of big data in company efficiency and shown in Figure 2.

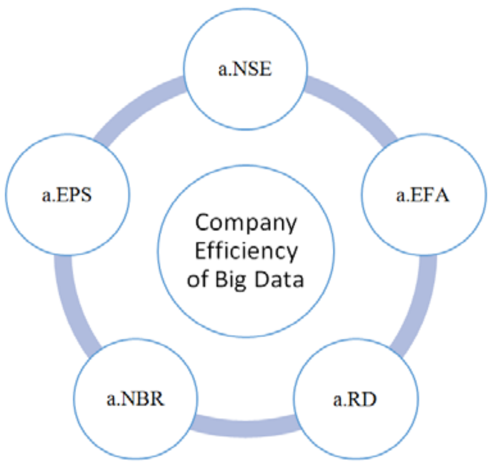

Figure 2. Model settings

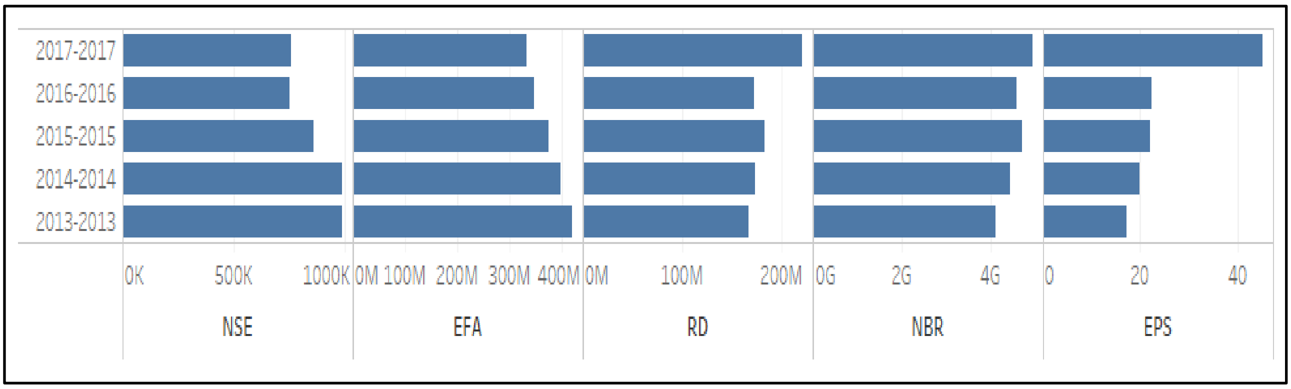

Figure 3. Big data analysis results

Table 6. The Annual Change Percentage for 2013-2017

Year	NSE	EFA	RD	NBR	EPS
2013-2014	0.02%	-4.96%	15.99%	7.33%	3.98%
2014-2015	-13.13%	-6.02%	9.69%	6.13%	5.28%
2015-2016	-12.14%	-7.31%	2.05%	-2.49%	-5.30%
2016-2017	0.66%	-4.05%	101.12%	7.60%	27.63%

We will conduct DMM model for all its have efficient companies. What it more, its hope to found out the factors and future trends of common transformation. In this study, a total of four companies successfully transformed steps (TE=1). The four companies are Hon-hai, Ares, Yulon, and Micro-stra. Through the DMM model discovery and as shown in Figure 3 and Table 6, we found that these companies have the characteristics.

1. NSE: The number of employees in these companies is decreasing year by year.
2. EFA: The expense of fixed assets in these companies is decreasing year by year.
3. RD: The R & D expenses of these companies have an increasing trend.
4. NBR:The EFA of these companies has an increasing trend.
5. EPS: The EPS of these companies has an increasing trend.

According to the results of the above DMM model and shown in Figure 2 and Table 6. We can have found that the company's transformed steps have transformed its OEM model into developing RD model. According to the analysis, the company has transformed the product line model directly caused by the NSE plunge by 12.14 percent this 2015-2016. So, this company reduces the NSE put into the product line. Instead, these companies increased RD expenses. Due to the reduction of labor costs, the EFA was reduced, and NBR increased. As a result, the EPS after the transition increased significantly. For example, the EPS industry grew by 27.63 percent, and the EFA decreased by 5 percent this 2016-2017. And the transformation of its traditional industries to RD and manufacturing.

Furthermore, our findings are not in contradiction with those of the empirical studies discussed. These findings are consistent with the Shein [3] study that the importance of AI talent. Thus, so if the companies looking to make good on the promise of AI. It showed the companies appear to need more AI talent. We speculated that if the companies successfully transformed steps. Because they were increased RD expenses. Due to the reduction of labor costs, the EFA was reduced, and NBR increased. As a result, the EPS after the transition increased significantly. Hence, the companies of the EPS after the transition increased significantly, and it can support the RD expenses. The companies will contribute to sustainable economic growth and is an important management tool to stimulate trading fund management to improve efficiency.

5. Conclusion

The analysis revealed that the management of performance and productivity helps increase organizational competitiveness and adds to the country's economic growth. In this study, we find that a total of four companies successfully transformed steps (TE=1). The four companies are Hon-hai, Ares, Yulon, and Micro-stra. Thus, companies' total efficiency value during the period under study is 1 (TE=1), indicating that if no environmental factors are considered, these companies need not make any improvements or adjustments in terms of resource allocation, management decisions, and output scale.

On the other hand, According to the results of the above DMM model. This company reduces the NSE put into the product line. Instead, this company increased RD expenses. Due to the reduction of labor costs, the EFA was reduced and NBR increased. As a result, the EPS after the transition increased significantly. For example, the EPS industry grew by 27.63 percent and the EFA decreased by 5 percent this 2016-2017. And the transformation of its traditional industries to RD and manufacturing. Thus, so if the companies looking to make good on the promise of AI. Showed the companies appear to need more AI talent. We speculated that if the companies successfully transformed steps. Therefore, they were increased RD expenses. Due to the reduction of labor costs, the EFA was reduced and NBR increased. As a result, the EPS after the transition increased significantly. So, these critical factors will help the enterprise to transfer its AI industry operation type successfully. Further, we discover that AI can be applicable to save employment and increase its short-term profit.

It was hope that this study can help the industrial operators to coordinate all of the critical factors of successful industrial transformation and make them consistent so that the enterprise may operate under the structure of the industrial core ideology and transformation goal, further, to merge the critical factors into all levels of the enterprise to become the goal, strategy, cultural intelligence, and related management actions, and to change the challenging mission of industrial transformation into a clear and feasible mission.

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