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Better practice prediction using neural networks: an application to the smartphone industry

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Abstract

Purpose – The purpose of this paper is to develop an artificial neural network (ANN) based prediction model via integration with data envelopment analysis (DEA) to provide the means of predicting incremental performance goals. The findings confirm the usefulness of the herein developed prediction approach, based on the results of analyses of time series data from the smartphone industry.

Design/methodology/approach – A two-stage hybrid model was developed, incorporating sequential measurement and prediction capability. In the first stage, a Chames, Cooper, and Rhodes DEA model is the preprocessor, generating efficiency scores (ES) of decision-making units (DMUs). In the second or follow-on stage, the ANN prediction module utilizes knowledge variables and ES to predict the change in performance needed for a desired level of improvement.

Findings – This combined approach effectively captured the information contained in the industry's turbulent characteristics, and subsequently demonstrated an adaptive prediction capability. The back propagating neural network successfully predicted the incremental performance targets of DMUs, which translated the desired improvement levels into actionable performance goals, e.g., revenue and operating income.

Originality/value – This paper presents an incremental prediction approach that supports better practice benchmarking. This study differentiates itself from previous research by introducing an adaptive prediction method which generates relevant quantity outputs based upon desired improvement levels. The proposed modeling approach integrates performance measurement with a prediction framework and advances benchmarking practices to enable better performance prediction.

Keywords Performance measurement, Benchmarking, Data envelopment analysis, Artificial neural network, Performance prediction, Smartphone industry

Paper type Research paper

1. Introduction

Coping with rapid rates of environmental change is a way of life in many industries. Increasing environmental complexity and competitive intensity make planning more difficult. These conditions are typical for firms grounded in technology and innovation, i.e., smartphone providers. In this turbulent, competitive environment, successful business outcomes are at least partially related to the expenditure of scarce resources, which poses a serious challenge to both leading and lagging firms. For these firms, maintaining their competitive advantage is instrumental to superior performance, and to defending against competitors efforts; both of which are minimum requirements for

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survival. Accordingly, constant effort is needed to maintain and extend their competitive edge. Because of the crucial need to succeed on both fronts, these firms' efforts are focussed on performance improvement via the execution of their established strategy; improvement in their cost structure, operational efficiency, and proficiency; and the promotion of knowledge creation and its translation into tangible business outcomes. Consequently, strategy-driven improvement becomes a core concern for improvement-conscious managers.

Each firm's position in their industry, along with their resources and chosen organizational strategy, brings us to the point of needing to ask the following questions, which are grounded in need assessment, i.e., "how much improvement do we need to make?"

Should the industry leader like Apple be the benchmark target to learn from?

If so, is it practically feasible and actionable for all firms?

Is it more realistic to pursue incremental improvement rather than

radical goals?

If so, how can we determine appropriate benchmarking targets for continuous improvement?

These questions prompted this study to use an artificial neural network's (ANN) predictive capability to enable better practice benchmarking. The mainstream benchmarking literature focusses on using best practices to trump competitors' performance (Dai and Kuosmanen, 2014; Estampe *et al.*, 2013; Hung *et al.*, 2010; Jain *et al.*, 2011). However, this approach might be sub-optimal when attaining best practice levels are too far beyond an organization's present capabilities. Due to firm-specific factors and the complex operating environment, the pursuit of best practices does not always lead to superior performance. There may not be a single best option suitable for the pursuit of continuous improvement and subsequent business excellence (Agarwal *et al.*, 2013; Francis and Holloway, 2007; Sousa and Voss, 2008). In fact, business necessity has promoted the development of flexible benchmarking approaches to support companies operating in a rapidly changing, turbulent environment (Gobble, 2013; McAdam *et al.*, 2008). In addition, despite contradictory views on best practices, the lack of a sound evaluation methodology has been a major challenge for the further development of this research stream (Francis and Holloway, 2007). With growing criticism of "best" practices in the face of the demands of business necessity, this research is aimed at developing a practical methodology to support better practice benchmarking. From this perspective, this paper fills the void of the demanding but less covered research area and bridges the gap between theory and practice.

This paper presents the approach of combining an ANN with data envelopment analysis (DEA) in support of better practice benchmarking. Empirical support of this approach is grounded in an empirical analysis using data collected from the smartphone industry. By combining the optimization capacity of DEA with the predictive potential of ANN, a complementary forecasting method is established, that is well suited to the incremental benchmarking advanced in this study. The resulting model enables better practice benchmarking, thus advancing the establishment of effective performance measurement and decision support systems.

The proposed model proved effective in empirical analysis of the smartphone industry data by capturing industry-specific characteristics regarding the use of knowledge creating resources and financial outputs as its inputs and outputs. The smartphone industry was considered appropriate as a test case for this study due to its rapidly changing, turbulent business environment (Connors, 2013; Rossi and Sandstrom, 2013; Vascellaro and Sherr, 2012). Knowledge resources and financial measures have been widely used as significant input and output variables to assess the performance of technology-oriented companies (Mudambi and Swift, 2014). To the best of the authors' knowledge, this is the first attempt to introduce incremental performance prediction using the combined DEA-ANN approach to the smartphone industry and beyond.

The remainder of this paper is organized as follows. In Section 2, we briefly review related studies. Section 3 outlines the DEA and ANN methodologies. Section 4 describes the data and variables used for this study, followed by a detailed discussion of the empirical analysis and results in Section 5. A brief conclusion and recommendations for future research are presented in Section 6.

2. Related studies

The pursuit of continuous improvement and the promotion of innovation have been considered the goal of performance benchmarking. To this end, firms strive to achieve competitive advantage over their competitors based on quality enhancement, technology advancement, and cost optimization (Anand, 2008). With increasing interest and extended applications, various definitions of benchmarking have been presented by researchers. These definitions commonly address a sequential process which includes a search for the best practice, comparative measurement, continuous improvement, and superior performance (Bogan and English, 1994; Camp, 1995; Cox *et al.*, 1997; Dai and Kuosmanen, 2014; Estampe *et al.*, 2013). Anand (2008) analyzed definitions of benchmarking and contributed this comprehensive definition of benchmarking to the literature:

> A continuous analysis of strategies, functions, processes, products or services, performances, etc. compared within or between best-in-class organizations by obtaining information through appropriate data collection method, with the intention of assessing an organization's current standards and thereby carry out self-improvement by implementing changes to scale or exceed those standards.

Conventional benchmarking is focussed on identifying best practices in terms of strategy, process, competitive advantage, performance, and other areas for improvement, which then become benchmarks for improvement-conscious firms seeking performance levels comparable, if not superior, to the industry best. In other words, "best performance" has become axiomatic in the superiority pursuing benchmarking process. According to the American Society for Quality, a best practice is defined as "a superior method or innovative practice that contributes to the improved performance of an organization, usually recognized as best by other peer organizations."

With the dominance of "best"-driven practices, the benchmarking concept has evolved to include a wider range of entities as benchmarking targets by taking better performance into account. Prasnikar *et al.* presented the benchmark concept to embrace "above-average" performers in addition to the best practices, thus defining benchmarking in more general terms as:

> […] a process of creating business knowledge by comparing and analyzing business information about other companies with the goal of improving the quality of decision-making.

Strong emphasis is put on whether benchmark analysis results can support quality decision making, thus facilitating actionable and achievable improvement. Under this premise, firms are motivated to learn not just from "best" practices but also from "better" performers. Furthermore, the pursuit of best practices may lead to the increased risk of poor decision making in some cases, as warned by Gobble (2013). Therefore, precautions need to be taken to avoid the "best practice trap," which occurs when seeking the best practice may not always yield the best results (Agarwal *et al.*, 2013; Francis and Holloway, 2007). According to Davies and Kochcar, best practices are any helpful measures that support "lower performers to pursue medium performance, medium performers to achieve higher performance, and higher performers to continue to be successful." However, in the midst of a benchmarking practice and literature dominated by "best practices," the conceptual development of better practice is still shallow and the lack of a proper evaluation methodology was pointed out as both a cause of this as well as a future necessity (Francis and Holloway, 2007). This research paper thus focusses on developing a sound methodology to support better practice by combining DEA and ANN as a complementary tool.

In the best practice benchmarking research, DEA has been widely used as a non-parametric modeling tool. DEA can identify best practice units and propose the necessary improvements needed for inefficient decision-making units (DMUs) to become users of best practices. DEA, as a deterministic extreme point method, lacks prediction capability; therefore, its application to solve forecasting problems is not found in the literature. This highlights its inability to support better performance prediction as a standalone technique. A rich literature on DEA is available and its applications include virtually all business disciplines, covering private and public organizations of varying scales. Detailed overviews of DEA applications are found in recent summary papers by Liu *et al.*

In comparison, the strength of ANN is in its predictive capacity. ANN, with its processing paradigm rooted in the biological neural system, has broad application areas as an intelligent information processing tool, including pattern association, function approximation, and forecasting. Despite proven and promising outcomes of ANN with growing applications, few reports have been found in benchmarking and performance measurement research. The literature shows a handful of ANN applications, but they are in conjunction with DEA. An attempt to combine ANN with DEA was conducted by Athanassopoulos and Curram (1996). The comparative study proposed the feasibility of ANN for measuring efficiency. Since then, exploratory studies have compared the suitability of using ANN as an alternative to DEA with varying results (Liu *et al.*, 2013a, b; Santin, 2008; Wang, 2003). Santin (2008) reported on ANN's strength to address nonlinear production functions, thus pointing out the potential advantages of ANN in predicting technical efficiency. More recently, Liu *et al.* (2013a, b) conducted an empirical study measuring the efficiency of 29 Taiwanese semiconductor companies, demonstrating ANN's capability to predict efficiency scores (ES).

Interestingly, comparative study results provide the potential benefits to be obtained by combing these two different methods in implicit or explicit terms. ANN has been used as a complementary tool for most DEA applications. This combined approach is motivated by the need to integrate the predictive capacity of ANN for data preprocessing, measurement improvement, and post-processing purposes (Emrouznejad and Shale, 2009; Pendharkar, 2011; Pendharkar and Rodger, 2003; Kheirkhah *et al.*, 2013). Emrouznejad and Shale (2009) and Pendharkar and Rodger (2003) used DEA as a preprocessor to screen training data for ANN to improve prediction accuracy and to save computational resources, respectively. Meanwhile, Pendharkar (2011) used ANN as a preprocessor to create data for DEA. Recently, Kheirkhah *et al.* (2013) in their application to predict electricity demand employed DEA as a postprocessor to select a suitable ANN model by measuring performance on different ANN prototypes. Even with varying experimental designs and limited attempts, previous studies demonstrated the successful application of this combined method in estimating production functions to predict ES. In this paper, a combined DEA and ANN approach is introduced to predict relevant and incremental quantity in terms of actual outputs (revenue and operating income in this setting) rather than predicting ES. Instead, DEA efficiency is used as a controllable pilot variable for the trained neural network to predict relevant outputs.

3. Methodology

3.1 DEA

DEA is a linear programming-based non-parametric analytical method. It has been widely used for assessing the comparative performance of DMUs in terms of efficiency. DEA, first introduced by Charnes *et al.* (1978), utilizes multi-dimensional homogeneous input and output variables and measures the relative efficiency of each DMU under evaluation. DEA, is a frontier technology (Farrell, 1957), calculating the weighted outputs over the weighted inputs of each DMU, then comparing results to the best practice to determine relative efficiency. In this way, DEA modeling develops an efficient frontier by connecting best practice DMUs, and assigning an ES of 1 to those DMUs on the frontier. The efficient frontier represents the functional relationships of efficient DMUs in producing potentially optimal output for any given input scale and envelops the rest of the DMUs under the frontier surface which are deemed inefficient. As deviations from frontier represent losses of efficiency, inefficient DMUs are assigned fractional efficiency indices less than 1.

Denote h_k as the CCR efficiency of kth DMU among n-DMUs which have r-input and s-output dimensions, then h_k can be determined by using following formula:

$$\text{Maximize } h_k = \frac{\sum_{j=1}^{s} o_j y_{jk}}{\sum_{i=1}^{r} q_i x_{ik}} \tag{1}$$

The above problem can be solved by transforming Equation (1) into a linear programming format as in following equations:

$$\text{Maximize } h_k = \sum_{j=1}^{s} o_j y_{jk} \tag{2}$$

s.t.:

$$\sum_{i=1}^{r} q_i x_{ik} = 1 \tag{3}$$

$$\sum_{j=1}^{s} o_j y_{jp} - \sum_{i=1}^{r} q_i x_{ip} \leqslant 0 \; p = 1, \ldots, n \tag{4}$$

$$o_j \cdot q_i \geqslant \rho > 0 \; \forall_{j,i}$$

where y_{jp} is quantity of jth output of DMU_p; x_{ip}, quantity of ith input of DMU_p; o_j, weight assigned to jth output; q_i, weight assigned to ith input.

Note that the maximization of h_k indicates the output orientation of efficiency measurement. However, the above problem can also be solved by focussing on minimizing weighted inputs, thus constituting an input-oriented model. Input-oriented modeling typically focusses on minimizing resource utilization to generate a given level of output. An output orientation approach emphasizes maximizing output assuming a given level of input. However, orientation itself is not considered a critical consideration with regards to results (Afzal and Lawrey, 2012). Orientation selection usually depends on the nature of variables and underlying constraints in conjunction with the purpose of the study and the characteristics of problems to be solved (Abate *et al.*, 2013). Since this research aims at estimating incremental performance outputs given the same level of knowledge inputs, the output orientation model is deemed appropriate. The CCR model is used as a preprocessor in the first stage of the experiment to produce the ES of the DMUs, and to generate data for neural net-based predictions in the second stage. The CCR model is one of the most popular models which has laid the theoretical basis for later variations, and is commonly used to test new theory and model development. For these reasons and the main scope of research on neural prediction, the CCR model is considered a suitable choice.

3.2 ANN

The ANN is an adaptive information processing system based on biological neural models where massive parallel processing elements, i.e., "neurons," provide the power needed to recognize key features or patterns in raw data through an iterative, corrective learning process (Fausett, 1994; Rumelhart *et al.*, 1986). Neural network learning can be broadly categorized as supervised and unsupervised, depending on the existence of targets corresponding to the incoming stimuli. Generally, nonlinear mapping and classification problems require supervised learning with the goal of capturing underlying input-output relationships, while unsupervised learning is better suited for application to clustering problems. For applications to predict outputs using seen or unseen inputs, as in this research, supervised back-propagation neural networks (BPNNs) have been most widely used. Figure 1 shows a simple 2-3-2 BPNN structure.

The BPNN learns the nonlinear functional relationships of input-output pairs through the weight forming mechanisms regulated by those neurons which are embedded in a hidden layer. Research results show that the addition of one hidden layer, thus constituting a three layered structure, can solve most nonlinear problems. The number of hidden neurons impacts learning outcomes by controlling the generalization of the network over training inputs. Indeed, the insertion of hidden

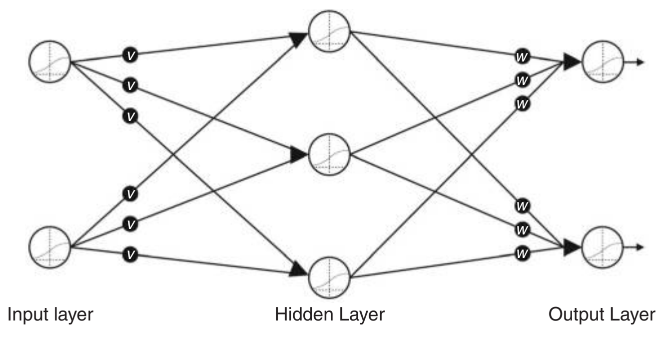


Figure 1.
A simple BPNN structure (2-3-2 network)

layers has provided a breakthrough in neural network studies, thus revitalizing ANNs since the late 1980s (Azadeh *et al.*, 2011; Ciampi and Gordini, 2013; Fausett, 1994; Pendharkar and Rodger, 2003). These hidden neurons assume an intermediary role by forwarding incoming signals and by propagating errors to backward paths. As shown in Figure 1, the hidden neurons calculate the weighted sum of net inputs (inner product of $X \bullet V$), and activate network output by applying transfer functions. The output of hidden neuron J can be determined by Equation (5). Following the activation of hidden neurons, output neurons receive the inner products of hidden output (H) and weight vectors ($\mathbf{W}$) and activate network outputs by applying transfer functions. The output of neuron K in the output layer can be found by applying Equation (6). In Equations (5) and (6), $f(\bullet)$ is a nonlinear transfer function that applies to the net outputs of hidden and output neurons. The sigmoid function, as in Equation (7), has been the most popular choice. At the end of the feed-forward process, the network calculates the sum of squared errors, denoted as E in Equation (8), by comparing target and actual outputs for each training input pair:

$$Y_J = f\left(y_{netJ}\right) = f\left(\sum_i X_i V_{ij}\right) \tag{5}$$

$$Y_K = f(y_{netK}) = f\left(\sum_j H_j \mathbf{W}_{jK}\right) \tag{6}$$

$$f(x) = \frac{1}{1+e^{-x}} \tag{7}$$

$$E = 1/2 \sum_o \left[T_o - Y_o\right]^2 \tag{8}$$

Upon completion of the information feed-forward and error calculation, the backward error propagation process minimizes E in a consecutive iteration process. This backward process functions to determine near optimal weight sets through sequential and gradual weight adjustment as controlled by the learning rate (ρ). Denoting $\Delta v_{i,j}(e)$ and $\Delta w_{j,k}(e)$ as weight changes for interconnecting neurons (i, j, o) in (input, hidden, output) layers at epoch e as in Equations (9) and (10), then new weights at epoch e+1 are determined by Equations (11) and (12) which address fractional adjustments controlled by ρ:

$$\Delta v_{i,j}(e) = -\frac{\partial E}{\partial v_{i,j}} \tag{9}$$

$$\Delta w_{j,o}(e) = -\frac{\partial E}{\partial w_{j,o}} \tag{10}$$

$$v_{i,j}(e+1) = v_{i,j}(e) + \rho \Delta v_{i,j}(e) \quad (11)$$

$$w_{j,o}(e+1) = w_{j,o}(e) + \rho \Delta w_{j,o}(e) \quad (12)$$

As discussed, network training is an iterative search process for sub-optimal weight sets, which preserve the functional relationships of training input and output pairs in a highly abstract form. The weight sets, obtained through the self-regulatory learning process, serve as a key to decode test inputs, which are often times unseen and noisy.

4. Data and variables

For this study, eight major Smartphone providers competing in the USA and global markets were selected: Apple (noted as APL in this paper), HTC (HTC), LGE (LGE), Nokia (NKA), Motorola (MOT), Research in Motion (RIM), Samsung (SMS), and Sony (SEM). These companies well represent the turbulent nature of the industry. Their performance reveals the intense competition between these companies, and the variation in competitive advantage of each company. As a consequence, each company strives to sustain its operations in a rapidly fluctuating and changing competitive environment. From this perspective, these companies are singularly focussed on performance improvement (Grundberg, 2012a, b; Luk, 2012; Robinson and Kendall, 2012). To capture these industry characteristics and to develop an adaptive prediction capability to support improvement initiatives, the new approach of using ANN with a DEA preprocessor is introduced. For this ANN-based modeling and analysis, publicly available data were collected from each company's annual reports between the periods of 2002-2012 inclusive, with SEM and LGE between 2006 and 2012, inclusive. Data for SEC and MOT for 2012 were not available due to the consolidation of their performance data into the results of the purchasing firms, Sony Corporation and Google, respectively. These merger and acquisition activities reflect the dynamic, rapid changes that are typical of the technology-oriented smartphone industry.

Competition in this industry is knowledge oriented and time sensitive. Actualizing knowledge initiatives into tangible performance outcomes is a critical factor for survival and growth. Under these premises, two knowledge creating resources, including intangible assets (IA) and R&D expenses, were used as input variables. IA were considered an important variable as they accounts for a firm's knowledge infrastructure while R&D expenses account for directed efforts (Mallick and Schroeder, 2005; Mudambi Swift, 2014). Two financial outcomes, revenue and operating income, were selected as performance outcomes. Revenue has been widely used as a crucial output variable representing the collective performance of a firm (Hsiang-Hsi *et al.*, 2013). However, revenue alone cannot fully capture the soundness of a firm's knowledge creation initiatives. In fact, during this observation period, 15 DMUs reported negative operating income. Given the position that the internalization of created value is not less important than the realization of return on committed resources, operating income is added to the output variables.

The resulting data set consists of 78 DMUs by forming two by two input-output pairs for each DMU. This data set was first utilized by the DEA model for the measurement of the relative ES of each DMU for preprocessing. Then the follow-on ANN predictor model uses IA and R&D expenditures as network inputs to predict two dimensional performance outputs, revenue and operating income. Table I shows the summary statistics of each variable and its usage in DEA and ANN models.

5. Experimental results

5.1 Empirical setting

The purpose of this research is to exploit the prediction capability of the ANN and examine its feasibility for better practice benchmarking in conjunction with using DEA as a preprocessor. As stated earlier, DEA has been widely used as a linear programming-based optimization tool capable of solving resource minimization or output maximization problems. In essence, achieving best practice performance levels is a primary reason for utilizing the DEA method. However, recent smartphone industry results prompt the fundamental question as to whether seeking to follow best practices is always the best decision. Differently put, is it logical for struggling firms to benchmark the best performer of the industry? For example, can Apple be the right benchmark for firms generating negative profits? In the sense of finding the most appropriate benchmarking choice, better practice benchmarking and supporting tools are becoming a practical business necessity. This requires the adaptive prediction capability and the capacity to handle negative numbers such as loss in profit and operating income. As it stands, DEA lacks both capabilities. The ANN-based complementary model is designed to overcome these issues and support better practice prediction. In this approach, the model predicts relevant output corresponding to a desired level of improvement. The experiments include a two-stage sequential process: DEA preprocessing and subsequent ANN prediction as depicted in Figure 2.

In the first stage, the CCR model receives two by two data streams to calculate CCR efficiency. In this setting, each company each year is treated as an independent DMU. Note that 15 negative numbered DMUs are not included in the DEA experiment, but saved as test input for the neural network prediction model in the second stage of the experiment. The resulting ES are then attached to the individual DMU and are used as key inputs for the ANN module. Therefore, the ANN prediction module is trained by using three input and two output variables.

5.2 DEA preprocessing for efficiency measurement

Table II summarizes the CCR model outputs which show an ES, a rank, and a reference set for each DMU under evaluation. The reference set in the fourth column represents efficient DMUs and becomes a benchmark target for each DMU. In this CCR experiment, three DMUs including APL2012, HTC2006, and LGE2007 show 100 percent efficiency, thus serving as benchmark targets for peer entities. This implies

	Intangible asset	R&D	Revenue	Op. income
Max	14,156	10,767	187,754	55,241
Min	1[a]	20	577	17[b]
Average	1,859	2,692	40,337	5,651
SD	2,965	2,834	42,781	8,893
DEA	Input	Input	Output	Output
ANN[c]	Input	Input	Output	Output

Notes: [a]Minimal value of 1 is assigned to HTC before it identified 5 in 2007; [b]15 DMUs with negative operating income is not included; [c]ANN uses DEA efficiency as an additional input

Table I. Summary statistics

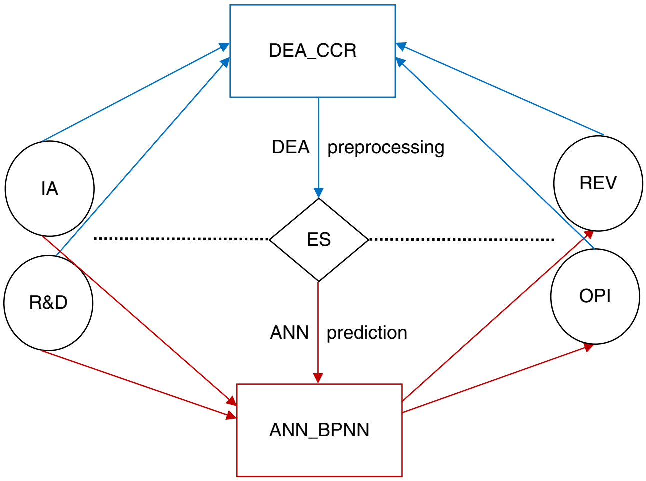


Figure 2.
Experimental setting and scheme

that Apple is the only company that achieved 100 percent efficiency in recent years, and Figure 3 clearly illustrates the superior efficiency of Apple against the rest of competitors.

As shown in Figure 3, Apple has attained consistent growth and improvement its efficiency since 2006 and has been the dominant industry leader for four consecutive years since 2009. Interestingly, DEA experiments using time series data capture the growing struggles of most incumbents since 2007 when Apple debuted as a new entrant. HTC's rapid decline and RIM's deepening struggle caused by its reduced sales and profit are observed from their efficiency trends. RIM first recorded negative profit in 2012. In the midst of the deteriorating efficiency of its peers, Samsung maintains its efficiency level, positioning the company in second place after Apple in 2012. Samsung reported the highest sales volume of $188 billion, followed by Apple's $157 billion in 2012. However, Apple has the highest operating income of $55 billion (35 percent of sales), more than twice as much as the operating income posted by Samsung, $27 billion (14.5 percent of sales). Samsung's overall efficiency in utilizing knowledge resources toward productization and internalization is far less than Apple's, as shown in Table II.

Nokia's consistent decline in efficiency is noteworthy. Nokia had long been an industry leader until 2010 on account of its superb performance in sales volume. Another look at its knowledge resource utilization, however, reveals that it had been maintaining low efficiency even before Apple's emergence and its knowledge resource efficiency hit rock bottom in 2012. Simply put, the company did not capitalize on its knowledge resources for new product development and technological innovation. Historically, Nokia's R&D expenditure has been a controversial issue for years. The company spent $1.4 billion for its own OS, Symbian, in 2010 prior to its transition to MS Windows. In comparison, Apple spent less than $800 million in R&D for their iPhone product (Srivastava and ben-Aaron, 2011). In 2012, Nokia invested $6.3 billion (15.8 percent of sales) in R&D whereas Apple expended only $3.4 billion (2.2 percent of sales), almost half of Nokia's absolute amount. The efficiency analysis speaks loudly that productivity, not volume, matters and that short-term tactics precede long-term strategy in the smartphone industry. From this perspective, the efficient utilization of

DMU	Score	Rank	Reference		
APL2012	1.0000	1	APL2012		
APL2011	0.9042	7	APL2012	LGE2007	
APL2010	0.8206	9	APL2012	HTC2006	LGE2007
APL2009	0.7123	11	APL2012	HTC2006	LGE2007
APL2008	0.6361	12	APL2012	HTC2006	LGE2007
APL2007	0.5465	15	APL2012	HTC2006	LGE2007
APL2006	0.4074	27	APL2012	HTC2006	LGE2007
APL2005	0.4609	20	APL2012	HTC2006	LGE2007
APL2004	0.3004	42	HTC2006	LGE2007	
APL2002	0.2201	48	HTC2006	LGE2007	
NKA2010	0.0917	61	APL2012	HTC2006	LGE2007
NKA2009	0.0829	63	HTC2006	LGE2007	
NKA2008	0.1212	60	APL2012	HTC2006	LGE2007
NKA2007	0.1824	52	APL2012	HTC2006	LGE2007
NKA2006	0.2469	45	HTC2006	LGE2007	
NKA2005	0.2360	46	HTC2006	LGE2007	
NKA2004	0.2053	50	HTC2006	LGE2007	
NKA2003	0.2021	51	HTC2006	LGE2007	
NKA2002	0.2290	47	HTC2006	LGE2007	
SEM2010	0.2108	49	HTC2006	LGE2007	
SEM2007	0.3018	40	HTC2006	LGE2007	
SEM2006	0.3277	36	HTC2006	LGE2007	
RIM2011	0.1520	57	APL2012	LGE2007	
RIM2010	0.3044	39	APL2012	HTC2006	LGE2007
RIM2009	0.3163	38	APL2012	HTC2006	LGE2007
RIM2008	0.3411	35	APL2012	HTC2006	LGE2007
RIM2007	0.3934	28	APL2012	HTC2006	LGE2007
RIM2006	0.3163	37	APL2012	HTC2006	LGE2007
RIM2005	0.2906	43	APL2012	HTC2006	LGE2007
RIM2004	0.1753	54	HTC2006	LGE2007	
RIM2003	0.1225	59	APL2012	HTC2006	LGE2007
MOT2010	0.0884	62	APL2012	HTC2006	LGE2007
MOT2006	0.1703	55	APL2012	HTC2006	LGE2007
MOT2005	0.1811	53	APL2012	HTC2006	LGE2007
MOT2004	0.1610	56	HTC2006	LGE2007	
MOT2003	0.1288	58	HTC2006	LGE2007	
HTC2012	0.3009	41	HTC2006	LGE2007	
HTC2011	0.5067	16	APL2012	HTC2006	LGE2007
HTC2010	0.5722	13	HTC2006	LGE2007	
HTC2009	0.4785	19	HTC2006	LGE2007	
HTC2008	0.4507	22	HTC2006	LGE2007	
HTC2007	0.9464	6	APL2012	HTC2006	
HTC2006	1.0000	1	HTC2006		
HTC2005	0.8583	8	HTC2006	LGE2007	
HTC2004	0.5043	17	HTC2006	LGE2007	
HTC2003	0.5648	14	HTC2006	LGE2007	
HTC2002	0.7816	10	HTC2006	LGE2007	
SMS2012	0.3731	31	HTC2006	LGE2007	
SMS2011	0.3509	33	HTC2006	LGE2007	
SMS2010	0.3687	32	HTC2006	LGE2007	
SMS2009	0.4481	24	HTC2006	LGE2007	

(*continued*)

Table II.
DEA experiment results

DMU	Score	Rank	Reference		
SMS2008	0.4393	25	HTC2006	LGE2007	
SMS2007	0.3473	34	HTC2006	LGE2007	
SMS2006	0.3831	29	HTC2006	LGE2007	
SMS2005	0.3740	30	HTC2006	LGE2007	
SMS2004	0.4281	26	HTC2006	LGE2007	
SMS2003	0.4557	21	HTC2006	LGE2007	
SMS2002	0.4980	18	HTC2006	LGE2007	
LGE2012	0.2606	44	HTC2006	LGE2007	
LGE2009	0.4487	23	HTC2006	LGE2007	
LGE2008	0.9517	5	APL2012	HTC2006	LGE2007
LGE2007	1.0000	1	LGE2007		
LGE2006	0.9709	4	LGE2007		

Table II.

Note: 15 DMUs with negative operating income were excluded

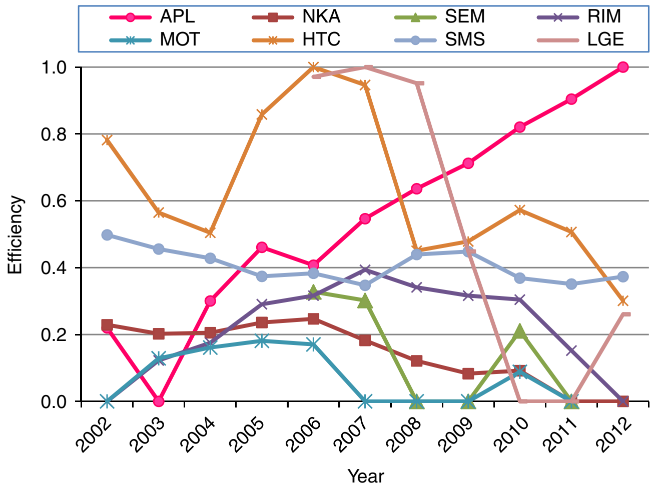


Figure 3. Efficiency trends of each company

knowledge resources and their actualization into tangible business outcomes carries a hefty weight for technology-oriented smartphone manufacturers. Further, efficiency trend analysis can provide early warnings to struggling firms.

5.3 Better performance prediction using ANN

ANN model building. The remaining discussion, then, turns to further elaboration on questions posed at the beginning. "Does Nokia need to target Apple as its benchmark just because Apple is the most successful peer?" Otherwise, "What is a practical and realistic performance goal for a struggling firm?" In other words, "How should firms approach to set their benchmark targets?" The application of the ANN model is designed for this purpose. It seeks solutions using the better practice approach. As shown in Figure 2, the neural network model receives CCR efficiencies from DEA preprocessing and the individual scores are jointly used with R&D and IA as input variables to train the neural network. After training, efficiency is used as leverage to stimulate the ANN model to generate a corresponding level of output. The desired level of improvement is represented in terms of an efficiency index. For this experiment, the NeuralWorks Predictor 3.1 simulator was used by utilizing its model building and data transformation capabilities. The network partitioned 63 DMUs into 44 (70 percent) and 19 (30 percent) for training and test, respectively. After ANN learning, the trained network conducted prediction tasks for those 15 negative-income DMUs which were excluded from DEA experiment and initial ANN training. For these unseen DMUs, the ANN demonstrated incremental prediction performance according to the desired improvement level, denoted by efficiency, assuming the same level of input resources. From a procedural perspective, the overall experiment can be summarized into the following sequential stages:

(1) DEA standalone process: DEA preprocess to produce ES of 63 DMUs for subsequent ANN prediction module using two input-two output variables.

(2) DEA-ANN sequential process: ANN training and test process to build the prediction model. DEA ES of 63 DMUs in the previous stage and two input variables are jointly used for model building to predict two outputs.

(3) ANN standalone process: ANN better performance prediction for 15 unseen DMUs based upon two inputs and desired performance (efficiency) level using the model.

Table III shows the ANN training results using three inputs (IA, R&D, ES) to predict two outputs (revenue and operating income). The resulting neural network comprises a 9-16-2 structure and demonstrated its performance by showing a high correlation between actual and predicted values. In predicting two dimensional outputs, the network showed somewhat higher R in predicting revenue (0.9788) than operating income (0.9148). This slight gap is hinted by less monotonicity in functional relationships between input and operating income output. In other words, for many DMUs, a scale of operating income did not follow increasing patterns of input quantity.

Figures 4 and 5 show ANN training results by displaying actual and predicted values of two output variables. Taking scale differences into consideration, each output is presented separately for clarity.

As the figures indicate, predicted outputs follow the patterns of actual revenue and operating income, a strong evidence of the model's generalization capability. The strength of the neural network resides in the generalization capability by learning from abstract relationships rather than from memorizing the specifics of each input. The figures reflect these characteristics. Note that the BPNN model used in this study is, in essence, a regression type of learning. Therefore, the network is less committed to the

	R	Avg. Abs.	Max. Abs.	RMS	Accuracy (20%)	Conf. interval (95%)	Records
Revenue							
All	0.9788	4,612	50,168	9,064	0.9841	18,036	63
Train	0.9897	2,612	15,751	4,321	1.0000	8,686	44
Test	0.9644	9,242	50,168	15,139	0.9474	31,834	19
Operating income							
All	0.9148	1,596	23,774	3,774	0.9841	7,509	63
Train	0.9125	631	4,119	1,064	1.0000	2,139	44
Test	0.8749	3,831	23,774	6,678	0.9474	14,042	19

Table III. ANN prediction results

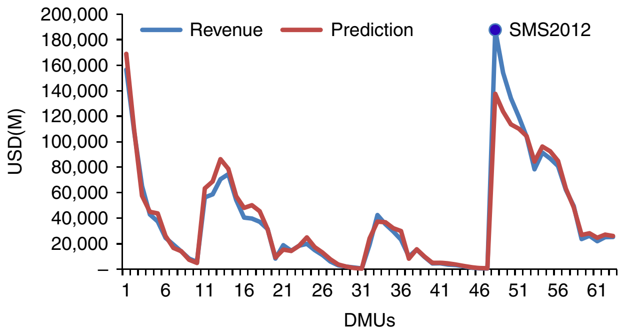


Figure 4.
ANN prediction of revenue

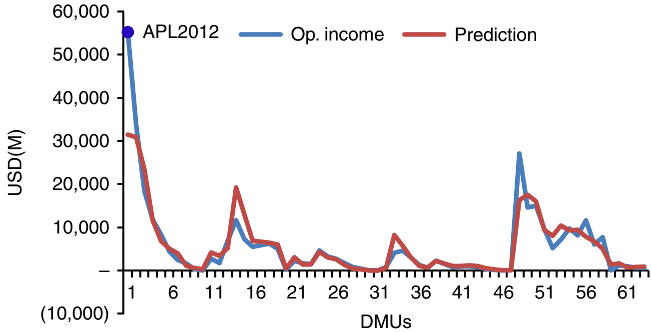


Figure 5.
ANN prediction of operating income

extreme or marginal values observed in SMS2012 and APL2012 for the prediction of revenue and operating income, respectively. These two companies reported unmatched figures in their revenue and operating income in 2012 as shown in Figure 6. The scatter plot in Figure 6 exhibits distributions of output variables of all DMUs.

Better performance prediction. The successful implementation of the BPNN and its proven performance with training and test data prompted this experiment of the incremental prediction of desired outputs in combination with revenue and operating

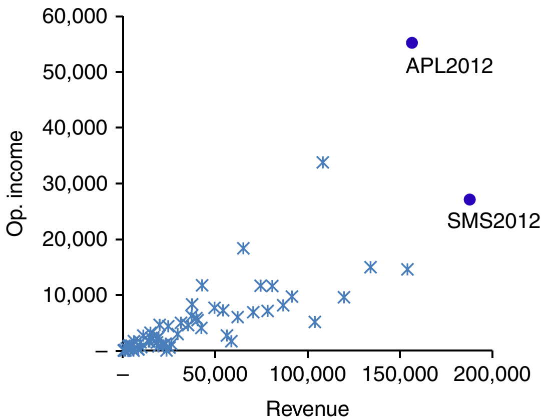


Figure 6.
Distribution of output variables (Revenue vs Op. income)

income. For this stage of analysis, the 15 additional DMUs previously unseen by the neural network were used. These DMUs had reported negative operating income and were excluded from the DEA experiment and ANN training, and were considered "0%" efficient. They are the DMUs that should most strongly seek improvement through the benchmarking process. The trained neural network preserves weight sets as a key code to predict matching outputs, upon presentation of these new data. As stated earlier, three input variables (IA, R&D, and ES) are used. By presenting varying ES for each DMU, the network predicts comparable output which becomes the incremental improvement target.

Figure 7 shows the experimental results for each DMU and displays the increasing patterns of the two outputs for each DMU in accordance with the increasing ES. In this

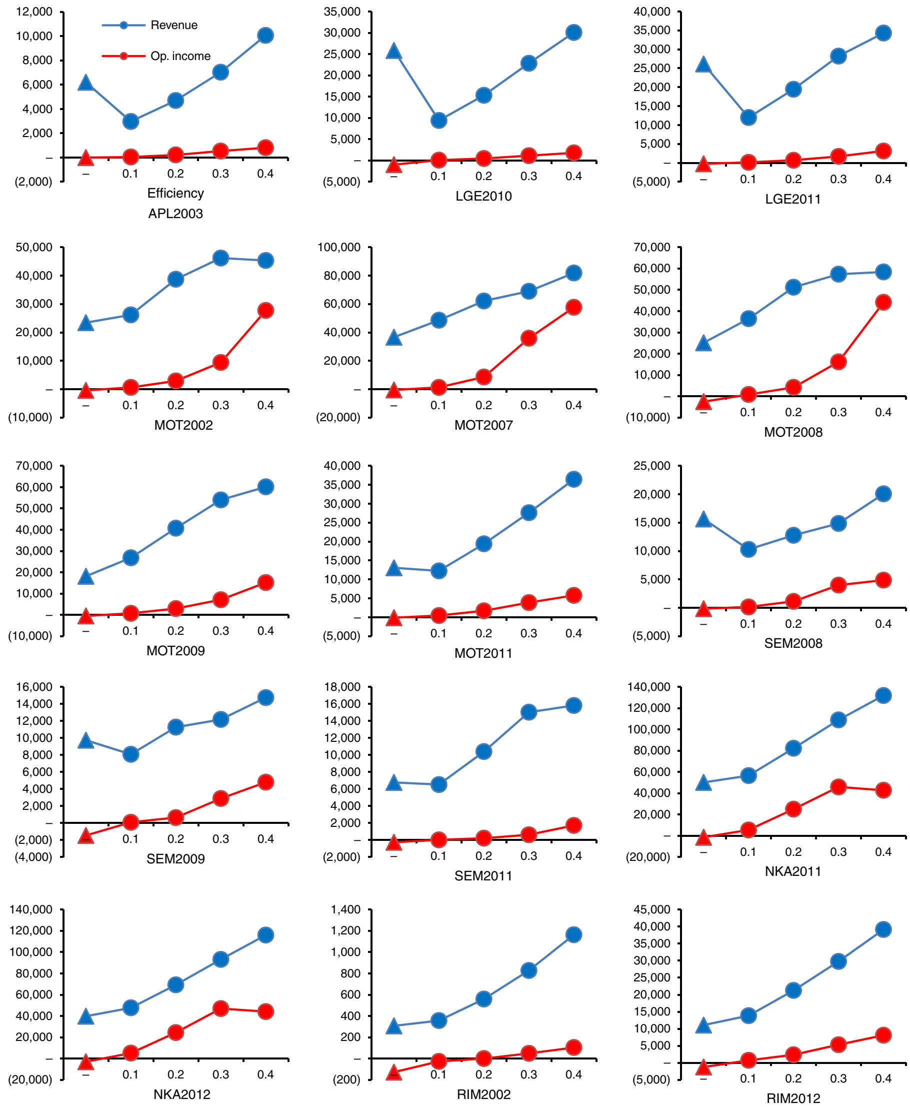


Figure 7.
ANN prediction for unseen DMUs

experiment, an ES of 0.4 was considered an effective range for the prediction task because the predicted output shows pairs of monotone increasing patterns for DMUs within the range. Given that the majority of DMUs had ES less than 0.5 (as observed in Table II), it is logical to expect that the recommendations from the neural network will be more effective for those DMUs having ES of less than 0.5.

Indeed, the performance of a neural network depends on its learning opportunities, that is, the number of exemplars from which to learn. To observe its impact on neural network learning, two controversial learning cases were further examined by conducting prediction with ranges up to the 1.0 efficiency scale. Figure 8 visualizes prediction performance for RIM2012 and NKA2012.

The figure shows that RIM2012 demonstrates increasing trends in revenue and operating income in proportion to the ES. Meanwhile, a disputable pattern was observed in NKA2012 from the efficiency scale of 0.4 and beyond. The distribution of input variables and learning cases displayed in Figure 8 provides hints for the causes of these differing prediction patterns. Unlike RIM2012, NKA2012 is sparsely populated, thus having limited learning opportunities, which becomes even more pronounced with DMUs having ES of 0.5 and above (refer to Figure 9). Simply put, NKA2012 had few exemplars to learn from. The same analogy can be applied to human learning paradigm in which ANN has its root.

By setting efficiency levels, each DMU can determine how much improvement it needs to make. Owing to the adaptive prediction capability of using a variable efficiency level, each DMU can establish an incremental improvement plan. In brief, this salient approach can help improvement-seeking managers with an intuitive answer to "What is the best way to start improving?" rather than "What is the best practice?" In so doing, this new method supports better practice benchmarking.

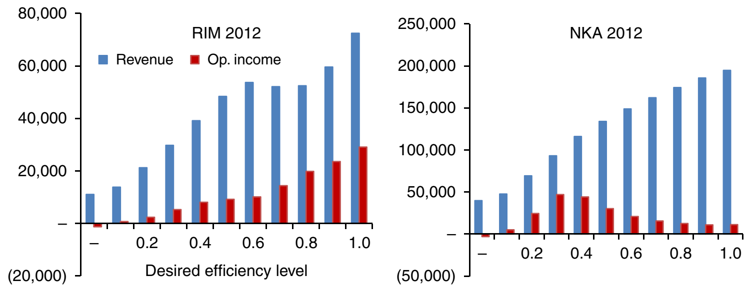
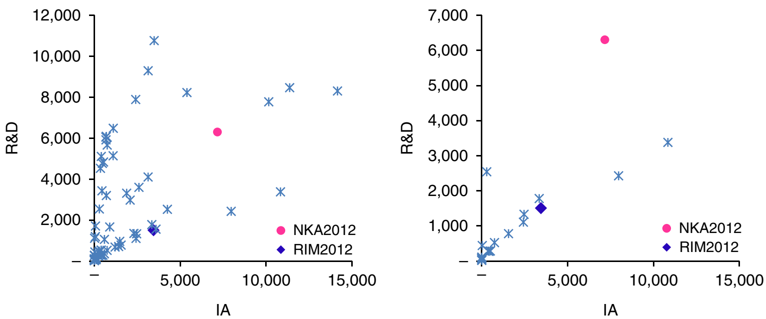


Figure 8.
Different learning cases



Note: All DMUs and DMUs with ES 0.5 and above

Figure 9.
R&D vs IA plot

Despite limitations in learning cases, the application of the neural network in addition to DEA proves its robustness in generalization and adaptive prediction capability over new data sets, and it demonstrates the potential for advancing performance measurement and benchmarking systems in today's turbulent business environment. The smartphone industry is known as a "perpetual motion" business with increasing product offerings and an evolving ecosystem. Operating under the conditions of this intensely competitive, technology-driven industry structure, sustaining competitive advantage is a daunting task regardless of current performance. As observed from comparative performance measured in the first stage of this empirical experiment, knowledge initiatives such as managing intellectual capital and R&D intensity are no longer long-range strategies in this fast-changing and technology-intensive industry. Rather, they are short-term tactics where capitalizing on valuable resources in a time-sensitive manner is a business imperative. Therefore, improvement-conscious firms should be vigilant regarding scanning for peer performance and continually adjusting their so-called SOPs by conducting reality checks on their planned actions. From this perspective, the demonstrated prediction mechanism provided by adopting neural network-based analytics will enlighten the path of improvement by proposing a feasible option, as we term it, better performance prediction.

6. Concluding remarks

This study explores the potential capability of a DEA-ANN approach as a vibrant incremental benchmarking prediction tool and demonstrates the successful implementation of the combined model based on an empirical analysis of the smartphone industry over the period of 2002-2012. The results of this research highlight the promising performance of the ANN-based prediction model. In this research, a combined DEA-ANN modeling approach is presented. In this underrepresented research avenue, a few previous attempts to integrate two methods have been made with major applications to estimate production functions via efficiency prediction (Azadeh *et al.*, 2011; Hsiang-Hsi *et al.*, 2013). Even compared with the rare applications of this combined approach, the present study fills a research gap in that the proposed model predicts actual quantities of output variables thus overcoming the limitation of the past approach of predicting ES only. In this two-stage process, DEA efficiency produced in the first stage serves as a key neural input mixed with knowledge resources to leverage a desired performance level. With this design scheme, the hybrid model extends the previous combined model for best prediction to support better practice benchmarking, thus enabling incremental improvement initiatives (Kwon, 2015). The encouraging performance of the proposed model highlights the bright potential of ANN and its hybrid system for benchmarking applications.

The contribution of this paper is threefold. First, the proposed method and its successful implementation, at its core, advances conventional superiority-driven performance measurement and the benchmarking framework to incorporate better performance prediction. In today's dynamic business environment, there is a growing notion that best practice may not be a single strategy. Rather, the selection of appropriate ways contingent on firm-specific situations is deemed more appropriate in many cases (Agarwal *et al.*, 2013; Francis and Holloway, 2007; Lu *et al.*, 2011; Prašnikar *et al.*, 2005). By presenting a sound methodology to support better practice, this research paper fills the research gap and advances benchmarking practices. Second, the proposed model can support managers' efforts to establish phased improvement goals by providing more viable and practical options. In addition to phased improvement planning, the model can support managers needing to make sound decisions, via the adaptive prediction capability to test potential scenarios during the planning, implementation, and monitoring stages. Distinguished from previous DEA-ANN applications, the combined model predicts an actual quantity of needed output instead of the indirect measure of an ES. With the notion of incremental, specific improvement targets, managers can launch actionable improvement initiatives within the reach of firms' capacity and in line with strategic intent as well. Third, the proposed model was successfully applied to the turbulent smartphone industry by utilizing knowledge variables as a key driver to generate tangible performance outcomes. Knowledge creation and its impact on business outcomes has been an important issue in the technology-oriented industry and the literature shows a positive linkage between these variables (Mudambi and Swift, 2014; Wang *et al.*, 2013). This research demonstrates the effectiveness of the model in the application of the smartphone industry by exploring the performance link between knowledge resource and financial outcomes. The presented approach can be further expanded beyond smartphone industry in the future.

This paper is not without limitations, as is the case in other studies. The limitation of this research lies in the availability of data. Due to limited access, additional industry data could not be obtained for additional analysis at this time of research. However, despite posed limitations, variables used in this study suffice for fulfilling the objective of this prediction modeling and empirical study. Future research can extend this study to further investigate the impact of knowledge resources on intermediate performance outcomes and intermediate performance to final outcomes upon the availability of data. For example, knowledge creating resources can be used as first stage inputs to produce knowledge outputs (i.e. number of patents, patent citation, and technology strength). These intermediate variables can then be paired with final performance outcomes, which may include financial measures (i.e. revenue, profit), production performance (i.e., number of new product, time to market), and market performance (i.e., brand equity, market share) (Chen and Chen, 2012; Gunday *et al.*, 2011; Wang *et al.*, 2013). Extended industry-level analysis will produce interesting research outcomes as well. For example, predictive analysis on different sectors within the information, communication, and technology industry will be a possible future research option.

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