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Evaluating the operational performance of knowledge-based industries: the perspective of intellectual capital

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Abstract Performance evaluation is more than a quantitative concept but should also take industrial characteristics into account in order to form an accurate evaluation. In the past, evaluations of the operational performance of knowledge-based industries have missed out a significant factor, which is intellectual capital (IC). By adopting data envelopment analysis (DEA), a multiple-objective decision making method, this study aims to construct an efficiency evaluation model for the Taiwanese digital content industry based on the perspective of IC. The empirical results suggest that the scale of the digital content companies does play an important role in influencing the operating efficiency. The firms have a small amount of capital can still attain optimal efficiency, from the perspective of IC. In addition, human resource capital and customer capital are the most significant influential factors that deserve digital content firms' attention. It is suggested that enterprises in the digital content industries should focus more on managing their IC. DEA can provide the semiconductor firms' operations with insights into resource allocation and competitive advantage as well as help with strategic decision-making.

Keywords Performance evaluation · Data envelopment analysis (DEA) · Digital content industry · Intellectual capital (IC)

1 Introduction

Confronted with the challenges of the twenty-first century, which is an era of knowledge economy as well as of globalization, many countries have made the development of knowledge

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economy a priority in terms of policy and a national goal. When the time comes, knowledge-intensive industries will replace the traditional capital- and labor-intensive industries and will enter the economic mainstream (Whittington et al. 2009). Therefore, countries across the world are aiming to increase their economic growth and maintain their competitiveness in terms of these emerging industries. While most of the developed countries are competing to transform their industries first, the digital content industries have become the top knowledge-based industries within the current knowledge economy era. Faced with the changing trends in the global economic paradigms and in an attempt to promote its national competitiveness, Taiwan has begun to develop its high value-added knowledge-intensive industries as part of a major developmental program.

The knowledge output of digital content industries mostly takes the form of intangible assets. Intellectual capital (IC) can greatly increase the general effectiveness and efficiency of firms which were established on the basis of tangible physical capital, and gives meaning to the digital content industry. However, the digital content industry as a whole is still in its preliminary development phase. Firms within the digital content industry are faced with many challenges in terms of the acquisition of skills and capital. If these firms want to increase their operational skills and obtain the research and development (R&D) capital from the financial market, it is not an easy task. Therefore, how to properly distribute and use limited resources in order to ensure the sustainable operation of an organization has become the main question that organizations need to address.

Since a firm's IC performance management is a complex phenomenon requiring more than a single criterion to characterize it, traditional performance measurement techniques have often been criticized for being inadequate. An appropriate evaluation of an organization facilitates the improvement of its operational performance. Chames et al. (1978) proposed the non-parameter planning method. Afterwards, DEA has become a popular method which is used for the analysis and evaluation of input efficiency and output performance. Researchers have adopted DEA in order to measure the performance of R&D projects and knowledge-based industries, such as the semiconductor industry (Chen and Chen 2007; Liu and Wang 2008; Lu and Hung 2010), the information industry (Chen and Iqbal Ali 2004; Thore et al. 1996; Uri 2003; Lu and Hung 2011), the medical and pharmaceutical industries (Pilyavsky et al. 2006; Wu et al. 2008), and so on. The results of these studies have all shown that DEA can be an effective tool in measuring an organization's knowledge capability and the performance of technological R&D. Therefore, in this study, DEA will be used as the method for evaluating the operational performance of knowledge-based industries in order to provide reference data to the relevant enterprises for the improvement and execution of their organizational performance.

Performance evaluation is not only a quantitative concept for multi-object decision making, but must also take into account the concept of industrial characteristics in order to form better-qualified evaluation results regarding the operational performance of an organization. Due to the fact that the digital content industry is a new and emerging industry, the relevant literature appears to be insufficient (O'Regan and Ryan 2010), particularly with regard to an overall performance evaluation of the industry. Moreover, IC is critical in terms of its influence over industrial performance, and the normal method of financial measurement is unable to integrate IC into an evaluation of the overall performance of an organization. Hence, based on the perspective of IC, this study will investigate how the digital content industry should be analyzed. The content of this paper will be presented in the following order: a literature review (Sect. 2), the research design (Sect. 3), the results of the empirical analysis (Sect. 4) and conclusion (Sect. 5).

2 Literature review

2.1 The Taiwanese digital content industry

According to the definition set down by the Digital Content Industry Promotion Office of Taiwan's Industrial Development Bureau (part of the Ministry of Economic Affairs), digital content is a product or service that digitalizes and integrates photographs, text, videos or linguistic data via information technology. The digital content industry can be divided into eight categories, including digital games, content software and e-learning, etc. According to the Almanac of Taiwan's Content Industry, the overall estimated output value of the Taiwanese content industry in 2009 was approximately 460.3 billion NT dollars, which is 14.96% more than that in 2008 (approximately 400.4 billion NT dollars more). Compared with the growth rate in 2008, the growth rate in 2009 increased by 3%, meaning that the Taiwanese digital content industry is growing steadily.

In terms of industrial characteristics, the content of their products is the center of the digital content firms' competitive advantage, and creativity is a critical element of the industry. The digital content industry depends heavily on the results of brainstorming between personnel from different fields, meaning that it is a creativity-intensive industry, implying that human resources is the most important form of capital of this industry. Technology is a necessary medium for materializing the product content of the digital content industry; continuous innovation is necessary in order to effectively convert intangible creativity into tangible products. Thus, a digital content service provider's innovation capital represents its potential for future development. The digital content industry needs to intensively interact with its consumers in order to develop products and services that match the needs of the local culture. In other words, the consumer capital established through brand management, which strengthens the firm's image within the minds of the customers and promotes its relationships with the customers, is vital to digital content firms. Therefore, IC is a critical competitive advantage for digital content firms, and plays an extremely important role in the digital content industry.

2.2 Intellectual capital

2.2.1 Definition and connotations of intellectual capital (IC)

Since the early years of the 1980s, IC has received a great deal of attention in the field of management research. Following on from the arrival of the knowledge economy era, scholars and managers gradually began to view enterprises' intangible assets and IC as critical factors in terms of the companies' profitability and competitive advantages. Thus, more and more scholars began to dedicate themselves to the study of IC.

Stewart (1997) suggested that IC is the sum of the knowledge and competences of each individual in the firm, that together can create a competitive advantage. Edvinsson and Malone (1997) stated that IC is what a firm holds in terms of knowledge, practical experience, organizational technologies, customer relationships and professional skills, which the organization may use to increase its competitive advantage in the market. IC is a concept that cannot be described in practical terms, and there is currently no generally acknowledged definition of the term. Scholars have different perspectives with regard to the connotations of the term "intellectual capital", which include human resource capital, structural capital and customer capital (Edvinsson and Malone 1997; Stewart 1997). Structural capital includes innovation capital and process capital; based on distinctive research goals and research objectives, some scholars have emphasized innovation capital, while others have focused on the importance of process capital, meaning that structural capital is then conceptualized differently. The connotations of customer capital and relationship capital are similar ideas, which generally indicate the firm's interactive and communicative relationships with outsiders. Therefore, this study, in accordance with the characteristics of the digital content industry, will focus on the development of indicators for measuring: (1) human resource capital, (2) innovation capital, (3) process capital, and (4) customer capital.

2.2.2 The measurement of IC

The measurement of IC includes aspects of overall assessment methods and the evaluation of different forms of capital. An overall assessment is an overview of a firm's value in terms of its IC, including its share of the market value and book value, its Tobin's Q value, its calculated intangible value (CIV), and so on (Stewart 1997). Previous studies on individual capital have mostly focused on the development of measurement indicators. Edvinsson and Malone (1997) proposed 111 key indicators for the measurement of global IC, including finance-oriented indicators and indicators of the organization's total assets, the operational revenue of new businesses, the revenue of each employee, the added value of each employee, etc. The customer-oriented indictors include the number of customers, the annual sales/number of customers, market share, etc. Human-oriented indicators include the number of employees, the average job seniority of the employees, the mean age of the employees, and so on. The indicators which are focused on process include the administrative expenses/total revenue ratio, and the administrative expenses/number of employees ratio. The renovation and development-oriented indicators include the ratio of R&D resources/total resources and R&D resources/administrative expenses.

The main purpose of this study is to construct an efficiency evaluation model using the perspective of IC. IC is critical for digital content firms if they are to survive and gain a competitive advantage. Therefore, in order to be consistent with the research goals of this study, the authors adopted an integrative but individual perspective.

2.3 DEA models

Data envelopment analysis is a nonparametric mathematical programming technique to solve an optimization problem subject to constraints (Lu and Hung 2010, 2011). It is commonly used to evaluate the relative efficiency of a number of DMUs. The basic DEA model in Chames et al. (1978), called the CCR model, has lead to several extensions, most notably the BCC. Consider a firm which produces s outputs ($r = 1, \ldots, s$) from m inputs ($i = 1, \ldots m$) and assume that there are n firms ($j = 1, \ldots n$). Let x_{ij} and y_{rj} be the amount of the ith input consumed and amount of the rth output produced by the$j$th firm, respectively. Let λ_j be a weight given to jth firm in the construction of the best practice frontier. Let s_i^- and s_r^+ be the input excesses and output shortfalls, respectively. Assume that the objective of each firm is to minimize its inputs, keeping the output level constant in the constant returns to scale (Chames et al. 1978). Technical efficiency (TE) of target firm$_0$ ($0 = 1, \ldots, n$) can be computed as a solution to the following linear programming (LP) problem:

$$
\begin{aligned}
& Min \quad \theta_o - \varepsilon \left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \right) \\
& s.t. \\
& \quad \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta_o x_{io}, \quad i = 1, \ldots, m, \\
& \quad \sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{ro}, \quad r = 1, \ldots, s, \\
& \quad \theta_o, \quad \lambda_j, \quad s_i^-, s_r^+ \geq 0; \quad \forall \;\; i \;\; and \;\; r; \quad \varepsilon > 0,
\end{aligned}
\tag{1}
$$

where θ_o is a scalar value representing a proportion of current inputs that can be used to produce the chosen level of outputs.

The LP problem is solved n times by varying the index ‘o’ over all firms. Each LP problem yields a set of solution values for θ, λ_j, s_i^-, and s_r^+. The optimal value of θ is its minimum value over all possible values of θ that satisfy the set of constraints in the LP problem and is the efficiency score for target firm$_0$, TE $= \theta$. If TE = one and all input and output slacks, s^- and s^+, are equal to zero, then the target firm$_0$ is technically efficient. If TE is smaller than one, then the target firm$_0$ is technically inefficient. The solution value of λ_j indicates whether the *j*th firm serves as a role model or peer for the target firm$_0$. If $\lambda_j = 0$, then the *j*th firm is not a peer. However, if $\lambda_j > 0$, say $\lambda_j = 0.3$, then *j*th firm is a peer firm with a 30% weight placed on deriving the target efficient output and input levels for the target firm$_0$.

If an additional constraint of $\sum_{j=1}^{n} \lambda_j = 1$ is imposed into Eq. 1, this suggests that the constructed best practice frontier exhibits variable returns to scale technology (Banker et al. 1984), i.e., the frontier permits increasing, constant and decreasing returns to scale (DRS). Hence, the efficiency score obtained from the modified LP problem reflects the target firm$_0$’s current scale of operation and is referred to as “pure” technical efficiency, denoted by PTE, representing the ability of management in transforming inputs to produce outputs. TE is the product of PTE and scale efficiency (SE), where SE for the target firm$_0$ is defined by the ratio of the SE = TE/PTE. It represents the proportion of inputs that can be further reduced after pure technical inefficiency is eliminated if scale adjustments are possible. If the ratio is equal to one, then target firm$_0$ is scale efficient and operating at the constant returns to scale region; otherwise, if the ratio is less than one, and then target firm$_0$ is scale inefficient and there is potential input saving through the adjustment of its operational scale. Whether the scale inefficient target firm$_0$ should be downsizing or expanding depends on its current operating region.

To determine the current operating region for scale inefficient firms, following the result of Zhu and Shen (1995), one can easily estimate the returns to scale (RTS) by the TE and PTE scores and $\sum_{j=1}^{n} \lambda_j$ in any optimal solution to the constant returns to scale. That is, if the TE = PTE, then constant returns to scale prevails; otherwise, if the TE $\neq$ PTE, then $\sum_{j=1}^{n} \lambda_j < 1$ indicates increasing returns to scale and $\sum_{j=1}^{n} \lambda_j > 1$ indicates DRS.

To recognize the inputs/outputs that are most important or to distinguish those efficient firms which can be treated as benchmarks, the benchmark-share measure (Zhu 2003) is defined as a ranking measure by combining the factor-specific measure and variable RTS model. Lewin et al. (1982) and Torgersen et al. (1996) reported the application for output-specific efficiency measures which are derived from radial component and non-zero slacks. Here, for a particular inefficient firm$_b$ the factor-specific (*k*th input-specific and *q*th output-specific) measure is via the following two linear programming problems and the existing variable RTS model’s best practice frontier.

The kth input-specific DEA model can be written as follows:

$$\begin{aligned}
&\theta_b^{k^*} = min \quad \theta_b^k, \quad b \in N, \\
&s.t. \\
&\sum_{j \in E} \lambda_j^b x_{ij} = \theta_b^k x_{kb}, \quad k \in \{1, \ldots, m\}, \\
&\sum_{j \in E} \lambda_j^b x_{ij} \leq x_{ib}, \quad i \neq k, \\
&\sum_{j \in E} \lambda_j^b y_{ij} \geq y_{rb}, \quad r = 1, \ldots, s, \\
&\sum_{j \in E} \lambda_j^b = 1, \quad \lambda_j^b \geq 0, j \in E
\end{aligned} \tag{2}$$

The qth output-specific DEA model can be written as follows:

$$\begin{aligned}
&\varphi_b^{q^*} = max \quad \varphi_b^q, \quad b \in N, \\
&s.t. \\
&\sum_{j \in E} \lambda_j^b y_{rj} = \varphi_b^q y_{qb}, \quad q \in \{1, \ldots, s\}, \\
&\sum_{j \in E} \lambda_j^b y_{rj} \geq y_{rb}, \quad r \neq q, \\
&\sum_{j \in E} \lambda_j^b x_{ij} \leq x_{ib}, \quad i = 1, \ldots m, \\
&\sum_{j \in E} \lambda_j^b = 1, \quad \lambda_j^b \geq 0, j \in E
\end{aligned} \tag{3}$$

In this instance, E and N respectively, represent the index sets for the efficient and inefficient firms identified by variable RTS model. The factor-specific measures in Eqs. 2 and 3 determine the maximum potential decrease of an input and increase of an output while keeping other inputs and outputs at current levels. These factor-specific measures are still multi-factor performance measures, because all related factors are considered in a single model.

3 Research design

3.1 Collection and selection of samples

The scope of this study mainly covered the firms in the digital content industry in Taiwan. In accordance with a publication by the Digital Content Industry Promotion Office of Taiwan's Industrial Development Bureau (part of the Ministry of Economic Affairs) named the Key Company Directory of the Digital Content Industry in Taiwan, 2006–2007, the authors selected the listed companies as the key source for the sample selection process. In addition, based on data from the Taiwan Economic Journal, invalid data such as insufficient information, missing records and information regarding firms focusing on non-digital-content business items were all removed from the database for this research. This was done to ensure the consistency and inclusiveness of the collected data. Moreover, the authors also referred to the Digital Content Industry White Paper published by the Digital Content

Industry Promotion Office of Taiwan's Industrial Development Bureau in 2005, which listed the main digital content firms in Taiwan, when modifying the scope of the sample. In the end, information regarding 21 firms was selected and obtained for the data sample for the purposes of this study.

3.2 Selection and definition of variables

The research results of the studies by Wu et al. (2006) and Edvinsson and Malone (1997), in terms of suitable measurement indicators of IC, have frequently been adopted by other researchers. The indictors which they developed vary due to the distinctive IC of different industries. Therefore, with regard to the characteristics of the industry in question, the authors decided to use human capital, innovation capital, process capital and customer capital as the main themes for the development of this research. In addition, taking into account the factors of the availability and objectivity of the data and the consistency with the DEA method in terms of the presumed isotonicity, the authors selected four input variables: the number of employees, R&D expenses, administrative expenses and advertisement expenses. The selected output variables are: net revenue and stock of IC. The purpose of selecting these variables is to present in full the operational performance of digital content firms from the perspective of IC. The selected variables, including the input and output variables, are depicted in detail in the following section.

3.2.1 The number of employees

This is the total number of employees of the sample company over a year. The core value of the digital content industry is significantly dependent on the attractiveness of the content, and therefore on an endless process of creativity. According to the industrial white paper of 2005, owing to the particularity and novelty of digital content, the manpower supply in the digital content industry is still a problem; more than half of human resource supply is lacked. Moreover, the Taiwanese government has continuously pushed for a human resource development program for the digital content industry, which indicates that the governmental believes that there is an urgent demand to foster the development of digital content personnel. Therefore, this study includes human capital as one of the constructs for analysis, and uses another construct, the number of employees, to measure each firm's existing human capital.

3.2.2 R&D expenses

This refers to the R&D expenses listed in the financial reports. The service content of the digital content industry is to produce different kinds of content and materials and manipulate them into new forms of data for consumers (the process of transforming traditional data into digital data). Therefore, regardless of whether the focus is on materials, content, product innovation or the development of relevant critical technologies, firms need to invest a great deal in R&D. This is why the authors have included innovation capital as one of the constructs for analysis, and converted R&D expenses into an indicator for measurement.

3.2.3 Administrative expenses

This refers to the administrative expenses listed in the company's profit and loss statement. Edvinsson and Malone (1997) suggested that the process indicator is not only for measuring the performance of the process, but also for assessing the valuable contributions arising from the productivity of the firm. Thus, this study utilizes administrative expenses as an indicator in order to evaluate the process capital of firms, in order to assess the overall operational performance of the digital content industry.

3.2.4 Advertisement expenses

This refers to the advertisement expenses listed in the company's financial reports. The digital content industry provides knowledge-based services. Therefore, the firms' interaction with their customers is critical. This study includes customer capital as one of the constructs for analysis. However, it is not an easy task to objectively assess customer capital. Following on from other researchers' use of advertisement expenses as an alternative quantitative variable, this study also uses advertisement expenses in order to measure customer capital.

3.2.5 Net revenue

This refers to the income of firms obtained from sales of their products, minus the sales returns, sales discount and allowances, and therefore represents the recurring business activities in a year. This study uses net revenue as an indicator in order to measure the financial performance of enterprises.

3.2.6 Stock of IC

The authors measured the financial performance of the digital content industries in order to study the overall value of the industry. In addition, the authors utilized the CIV method to measure the monetary value of the overall IC, which facilitated the comparison of the financial data of different companies and will reveal the stock of IC. CIV presumes that the value of the stock of IC represents a company's competence in terms of beating its competitors who hold similar tangible assets. The procedure for the calculation is as follows (Stewart 1997):

(a) Calculate the average pre-tax profit (a) from the last 3 years;
(b) Obtain the average balance of the tangible assets (b) at the end of the period the three years beforehand, which is listed on the balance sheet;
(c) Divide the average pre-tax profit by the average balance of the tangible assets. The results represent the return on assets (ROA): (c) = a/b
(d) Calculate the average industrial ROA (d) from the last three years; If and only if the return on tangible assets of the company is greater than the return on tangible assets of the industry (i.e. $c > d$) executing the method can be continued.
(e) Deduct the pre-tax profit from the product of the industrial average ROA and the balance of the tangible assets. The result is the excess return;
(f) Calculate the average income tax rate;
(g) Find out the after-tax profit of the excess return;
(h) Transfer the after-tax profit of the excess return into the present value; this equals the intangible asset value.

Table 1 Correlation coefficients among input variables and output variables

	Input variables				Output variables	
	x1	x2	x3	x4	y1	y2
The number of employees (x1)	1.000					
R&D expenses (x2)	0.948	1.000				
	$p=0.000$					
Administrative expenses (x3)	0.932	0.956	1.000			
	$p=0.000$	$p=0.000$				
Advertisement expenses (x4)	0.912	0.928	0.926	1.000		
	$p=0.000$	$p=0.000$	$p=0.000$			
Net revenue (y1)	0.964	0.665	0.989	0.949	1.000	
	$p=0.000$	$p=0.000$	$p=0.000$	$p=0.000$		
Stock of IC (y2)	0.949	0.674	0.986	0.940	0.967	1.000
	$p=0.000$	$p=0.000$	$p=0.000$	$p=0.000$	$p=0.000$	

4 Empirical analysis

4.1 Correlational analysis and descriptive statistics

The input and output variables selected by the DEA method should be consistent with the requirement of isotonicity, meaning that as the number of inputs increases, the number of outputs cannot be decreased. This also means that if there is a negative correlation existing between the input and output variables, the correlated items need to be removed in order to move on to the next stage of DEA. Therefore, the authors first tested the Pearson correlation of the input and output items in order to ensure that the data collected were isotonic, as required. Table 1 presents the results of the correlation analysis for a sample of 21 firms in 2005.

Table 1 shows that the input and output variables are positively correlated, and that the data collected meet the requirements of DEA theory. The four input variables (the number of employees, R&D expenses, administrative expenses and advertisement expenses) and the two output variables (net revenue and the stock of IC), through an appropriate selection process, can be further tested for their efficiency in terms of DEA. Table 2 presents the simplified descriptive statistics for the input and output variables of the 21 sample firms in 2005.

4.2 Efficiency analysis

First, the authors used the CCR model in order to obtain values for the total efficiency (TE) of a decision-making unit (DMU), and the BCC model (overall production efficiency = pure technological efficiency (PTE) $\times$ SE) to obtain the pure technology and SE values and to observe the RTS of the DMU, the reference set and the frequency. The results of the analysis are presented in Table 3.

4.2.1 Efficiency analysis using the CCR model

The CCR model functions by assuming that the scale return is a fixed number. Table 3 reveals that of the 21 sample firms, 10 companies achieved the value of 1.0, which represents

Table 2 Descriptive statistics for the 21 firms

Variables	Mean	SD	Valid *N*
Input variables			
x1: The number of employees (person)	447.19	712.34	21
x2: R&D expenses (NT$ thousand)	83348.33	75798.73	21
x3: Administrative expenses (NT$ thousand)	237749.00	708710.47	21
x4: Advertisement expenses (NT$ thousand)	49054.81	94613.21	21
Output variables			
y1: Net revenue (NT$ million)	3173.67	9008.48	21
y2: Stock of IC (NT$ million)	59816.01	45752.52	21

Table 3 Efficiency scores of 21 firms' performance model

No.	Firm	TE (CCR)	PTE (BBC)	SE	RTS	Reference group	Frequency
D1	Softstar	0.20879	0.77811	0.26832	DRS	D8, D10, D15	0
D2	InterServ	0.95141	0.98969	0.96132	DRS	D13, D14, D18, D19	0
D3	Wayi	0.40214	0.79411	0.50640	DRS	D8, D10, D15	0
D4	Soft-World	0.95009	1.00000	0.95009	DRS	D4	1
D5	M-etel	0.77466	0.90616	0.85488	DRS	D8, D14, D15	0
D6	Gamania	0.26166	0.53288	0.49102	DRS	D8, D10, D15	0
D7	Deltamac	0.50600	0.83402	0.60671	DRS	D8	0
D8	Fullerton	1.00000	1.00000	1.00000	CRS	D8	9
D9	Eten	0.47431	0.86181	0.55037	DRS	D8, D10, D15, D20	0
D10	Far EasTone	1.00000	1.00000	1.00000	CRS	D10	7
D11	104	0.36767	0.95940	0.38323	DRS	D8, D10, D15	0
D12	ISSDU	0.29785	0.79835	0.37308	DRS	D8, D10, D15	0
D13	NewSoft	1.00000	1.00000	1.00000	CRS	D13	2
D14	Penpower	1.00000	1.00000	1.00000	CRS	D14	3
D15	CyberLink	0.82965	1.00000	0.82965	DRS	D15	8
D16	PChome	1.00000	1.00000	1.00000	CRS	D16	1
D17	Hyweb	1.00000	1.00000	1.00000	CRS	D17	1
D18	iBMi	1.00000	1.00000	1.00000	CRS	D18	2
D19	G.T.	1.00000	1.00000	1.00000	CRS	D19	2
D20	DSC	1.00000	1.00000	1.00000	CRS	D20	2
D21	Ares	1.00000	1.00000	1.00000	CRS	D21	1
Mean		0.76306	0.92641	0.79881			

Note: *TE* PTE _ SE. RTS: *IRS* increasing returns to scale; *CRS* constant returns to scale; *DRS* decreasing returns to scale

full efficiency. The other 11 firms were comparatively inefficient, with a minimum value of 0.20879. The average TE value was 0.76306; meaning that the operation efficiency of the digital content industry in 2005 was 23.69%, which still leaves room for improvement. As for the firms which did not reach the required level of efficiency, researchers can analyze their efficiency further using different types of efficiency measurement model, and can explore the possible reasons for their inefficiency from the perspective of input factors and the optimal scale of production.

4.2.2 Efficiency analysis using the BCC model

The BCC model measures firms' PTE by assuming the varying RTS, in order to explore whether enterprises effectively utilize their input resources so that production can be maximized and input can be minimized. Finally, the results of the calculation of the PTE value represent the efficiency of the input variable; hence, the efficiency value will not be reduced owing to the fact that the DMU did not achieve the required optimal scale for the firm. Table 3 shows that of the 21 sample firms, 12 companies achieved the full efficiency value of 1.0, and nine companies had poor performance in terms of low PTE. The overall PTE value for the sample as a whole is 0.92641, and the minimum value is 0.53288.

In addition to the measurement of the PTE value, the BCC model can also calculate the efficiency of scale of the DMU, which represents the appropriate proportions of the input and output items of each DMU; a higher value stands for a more appropriate scale and level of productivity. Table 3 shows that there were 10 companies that approached full efficiency, with a scale value of 1.0. In addition, the average efficiency value for the overall sample was 0.79881. There were 11 DMUs with an efficiency value of less than 1.0. These companies need to adjust their input proportions in order to achieve the optimal scale of production, and the adjusting mode in accordance with the return to scale of a different DMU. As DRS takes place, the scale needs to be reduced. Otherwise, if there is in the increasing return to scale (IRS), the scale of the unit also needs to increase. The DMU stands for the constant return to scale (CRS), meaning that the firms are at an optimal status and do not need any adjustment. Table 3 reveals that in terms of the return to scale of firms, almost all of the companies which are less efficient in terms of return to scale are in the stage of DRS, and these companies need to decrease their scale of production in order to promote their overall production efficiency.

The reference set provides the necessary criteria for companies to refer to when they need to improve their PTE. Table 3 lists the reference set for nine non-efficient companies, which provides the criteria decision makers need in order to improve their company's efficiency. When the reference set of one DMU is referred to frequently by another DMU, the first DMU appears to be highly efficient. Table 3 shows that Fullerton (a digital technology company), which locates at the cutting edge of efficiency, was referred to by other DMU about eight times, meaning that it has reached optimal operation efficiency. The next most efficient companies were Cyberlink and Fareastone, which were referred to by other DMUs seven and six times, respectively.

For the 21 sample firms in the year 2005, their average PTE was 0.92641, which was higher than the average efficiency of scale 0.79881. This shows that the reason for the overall inefficiency was the inefficiency of the scale; therefore, the administrators must improve their TE through the adjustment and optimization of the scale of production. In a further investigation of the reasons for the companies' inefficiency, the authors found that the inefficiency of Softworld and Cyberlink arose from the inefficiency of the scale, meaning that both companies only need to adjust their scales in order to improve their efficiency. In addition, the other nine companies which were identified as being less efficient should also improve their scales and promote their capabilities in order to convert input resources into output productivity. In short, the research results of this study suggest that within the existing digital content industry, there are still many firms which need to adjust their scale of production and reconsider the proportion of their resources they invest in order to achieve optimal efficiency.

Table 4 The slack variable analysis of non-efficient firms

Firm	Input variables				Output variables	
	Employees (x1)	R&D expenses (x2)	Administrative expenses (x3)	Advertisement expenses (x4)	Net revenue (y1)	IC Stock (y2)
Softstar	148.43	0	0	10999.82	1891.17	0
InterServ	0	0	7922.84	0	12.75	0
Wayi	0	13731.62	0	14978.14	2146.61	0
M-etel	0	542.02	0	3905.24	730.44	0
Gamania	92.27	0	0	3650.81	2428.08	0
Deltamac	54	0	26541	45553	645.75	0
Eten	60.38	0	0	7869.29	0	0
104	286.22	0	0	29796.69	821.28	0
ISSDU	328.78	0	0	68344.01	515.97	0

4.2.3 Slack variable analysis

Through the results of the analysis using the BCC model regarding the PTE, Table 3 shows that within the 21 sample firms, there are nine non-efficient companies, meaning that these companies have not effectively utilized their input resources and so have not achieved the optimal situation with regard to output. Through the BCC model's slack variable analysis, researchers can obtain information about a firm's situation with regard to the utilization of their resources, and can therefore understand where there is room for improvement in terms of input and output resources. This can promote the firm's operational performance to approach the optimal efficiency value, which is 1.0 in this case.

Table 4 lists the input and output slack variables of nine non-efficient firms. These non-efficient companies can be improved through changes to the amount of resources they invest, such as by reducing the value of their inputs or increasing their output in order to effectively promote their efficiency. The information in Table 4 indicates that, with regard to the input items, most of the non-efficient companies should reduce their input in the form of advertisement expenses and their number of employees, because these companies need to promote their operational performance. The results of this study also indicate that most of the non-efficient companies need to improve their net revenue in order to achieve full efficiency; this is the key point that administrators need to pay attention to.

4.2.4 Sensitivity analysis

After examining the overall performance of the firms, the authors went a step further in exploring the effects of different input and output items from the sample firms' using the sensitivity analysis method. With regard to the input items, the authors removed one input variable each time, which then formed four new input–output variable models. Then, by comparing the efficiency of the newly generated model with that of the existing model, the authors were able to perceive the level of influence of each input item on the digital content industry, as well as the competitive advantages of different companies (Table 5).

With regard to the input items, the average efficiency value of the original model was 0.763. After deducting advertisement expenses, the average efficiency value becomes 0.592;

Table 5 The sensitivity analysis of 21 firms' performance model

Firm	TE (CCR)	Removed variable					
		Employees (x1)	R&D expenses (x2)	Administrative expenses (x3)	Advertisement expenses (x4)	Net revenue (y1)	IC Stock (y2)
Softstar t	0.209	0.168	0.209	0.208	0.171	0.074	0.184
InterServ	0.951	0.717	0.951	0.951	0.575	0.276	0.945
Wayi	0.402	0.229	0.402	0.402	0.383	0.088	0.402
Soft-World	0.950	0.793	0.950	0.950	0.775	0.850	0.365
M-etel	0.775	0.575	0.775	0.770	0.774	0.194	0.775
Gamania	0.262	0.241	0.262	0.262	0.140	0.248	0.104
Deltamac	0.506	0.506	0.470	0.459	0.506	0.347	0.497
Fullerton	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Eten	0.474	0.351	0.474	0.472	0.396	0.388	0.235
Far EasTone	1.000	1.000	0.925	1.000	0.478	1.000	0.105
104	0.368	0.368	0.263	0.261	0.368	0.267	0.326
ISSDU	0.298	0.297	0.278	0.238	0.298	0.290	0.165
NewSoft	1.000	1.000	1.000	1.000	0.508	0.882	1.000
Penpower	1.000	1.000	1.000	0.987	1.000	1.000	1.000
CyberLink	0.830	0.358	0.830	0.830	0.426	0.603	0.419
PChome	1.000	1.000	1.000	1.000	1.000	1.000	0.254
Hyweb	1.000	0.757	1.000	1.000	0.288	1.000	0.681
iBMi	1.000	1.000	1.000	1.000	1.000	0.393	1.000
G.T.	1.000	1.000	0.812	1.000	0.828	1.000	1.000
DSC	1.000	1.000	1.000	0.797	1.000	1.000	1.000
Ares	1.000	1.000	1.000	1.000	0.510	1.000	0.877
Average	0.763	0.684	0.743	0.742	0.592	0.614	0.587

the efficiency values of 13 of the DMU change, and more than half of the efficiency values of the digital content firms decline. For instance, the values of G.T. Internet Information, Newsoft, Fareastone and Hyweb all changed from their original 1.0 full efficiency status to non-efficiency, particularly Hyweb, which experienced the greatest variation. The rest of the firms also experienced some sort of variation after removing the advertisement expenses. After deleting the input item of the number of employees, the overall average efficiency value declined to 0.68. The efficiency values of a total of 10 DMUs changed, which is at the second place in terms of the variation of changes. The efficiency values of approximately half of the firms declined, such as Hyweb, for which the efficiency value changed from 1.0 (full efficiency) to the less efficient value of 0.757. After taking away the input variables of R&D expenses and administrative expenses, the influence of both items on the TE value was not apparent, demonstrating that these two items are both critical to every firm dealing with digital content.

In short, the 21 sample firms are the most sensitive with regard to the number of their employees and advertisement expenses. If we remove these two items, the efficiency values of the companies react significantly to the removal, meaning that these two items also influenced the output performance of most of the digital content firms, and could become critical elements in the operational performance of the digital content industry.

With regard to the output items, when exploring the efficiency values of a single output variable, the authors use the relevant analytical procedure involved removing only one of the output variables at a time for observation. The purpose of reducing one output variable each time is to compare the results of sensitivity analysis and the original value before the removal of variables in order to observe the effect of the removed item on the efficiency of the performance of different firms. The goal is to ensure the reliability and accuracy of the results of the analysis. Therefore, our analysis is divided into two models. One of the models is designed to analyze four input variables and one single output variable, the net revenue. The other model is designed to analyze four input variables and one single output variable, the stock of IC. The results of the analysis are shown in Table 5.

With regard to the output items, after removing the variable of the stock of IC, the companies that still presented a good performance in terms of their efficiency value tended to have optimal financial performance. However, this does not mean that those companies that performance well in terms of their stock of IC can be sure to receive similarly positive financial gain. In order to draw comparisons with the original model, it was shown that the newly generated model indicated that the number of DMUs with a full efficiency value of 1.0 declined from 10 to eight firms, including Fullerton, Fareastone, PenPower, PChome, Hyweb, G. T. Group, Data Systems and Ares. The average TE value of these firms was 0.61427. When deleting the item of net revenue, six DMUs had optimal performance in terms of their stock of IC; these firms were Fullerton, Newsoft, PenPower, IBMI, G.T. Group and Data Systems. Their average TE value was 0.58727; the variation in amplitude seems to be obvious, meaning that the items of net revenue and the firm's stock of IC have a significant effect on the operational performance of the digital content industry.

To summarize, different firms within the digital content industry have their own competitive advantages. Some of the companies are better in terms of their financial performance, while others perform better in terms of their stock of IC. The overall results of this analysis reveal that Fullerton has reached optimal efficiency, meaning that Fullerton uses its resources in an optimal way, based on the perspective of IC. Fullerton's efficiency not only reveals its financial performance, but also the monetary value of a stock of IC.

5 Conclusions

The main research goal of this study is to measure the operational performance of the digital content industry from the IC perspective. Considering the measurement of overall and individual IC, this study aimed to measure the overall operational performance of the digital content industry.

This study has contributed to describing the critical role of IC in the digital content industry. The authors utilized the IC perspective in order to objectively measure the efficiency of the operational performance of firms and to find out what was the most critical element in the industry. Through the measurement characteristics of DEA, the authors integrated more data concerning input and output, containing data on input resources and output performance, in order to analyze the TE of the operational performance of the firms in the sample. A measurement model was constructed which is suited to an analysis of the efficiency level of the operational performance of the digital content firms in Taiwan. These research results are able to offer enterprises strategic directions for the improvement of their administration and management. The focal points are summarized in the following section.

5.1 The profile of the operational efficiency of the digital content industry

Through the CCR model of the DEA method, researchers are able to obtain the efficiency value of different digital content firms and to judge the comparative efficiency of companies in terms of their input and output. The BCC model helps researchers to investigate the reasons for firms' inefficiency, or to find out the units of their inefficiency. The factors resulting in their inefficiency could be related to technology or scale. A reference set can provide a paradigm for the improvement of the efficiency of an inefficient unit. In addition, slack variable analysis can supply directions for firms wishing to reform their efficiency, so that administrators have access to information about the extent to which their input or output should be increased or decreased in order to achieve the optimal conditions. In the case of the TE, amongst the 21 firms, 10 are comparatively efficient, but the other 11 firms are inefficient, revealing that about half of the firms in the digital content industry still have room for improvement. The main reason for the inefficiency of these digital content firms stemmed from the inefficiency of their scale; digital content firms should pay much closer attention to adjusting their input resources, so that they are of an appropriate scale in order to prevent the waste of resources which can lead to a decline in efficiency. Through the selection of a reference set, enterprises can set up management goals as a way of directing management teams and motivating employees. Once the members of an organization share a common goal, the information contained within the goal can also be the most effective tool for mediating between administrators and employees, and can help to promote the operational performance of the firm. As for slack variable analysis, the results of the research show that the inefficient companies in this study should focus on controlling their advertisement expenses and number of employees.

5.2 The key factor affecting the digital content industry

According to the results of the sensitivity analysis, firms within the digital content industry are very sensitive to variations in the number of their employees and in their advertisement expenses. If the advertisement expenses are removed from the input variables, the efficiency values of more than half of the digital content firms appear to decline. If the item of the number of employees is removed, almost half of the firms undergo significant changes in their efficiency values. The authors used the number of employees to represent manpower capital, and advertisement expenses as customer capital, demonstrating that manpower capital and customer capital have a significant effect on the operational performance of digital content firms. Thus, manpower and customer capital can be viewed as critical elements in the digital content industry. The results of a great deal of research indicate that, in accordance with distinctive industrial characteristics, each industry has its own most important element in terms of IC. Companies which have different modes in operation generally utilize their IC in different ways. Therefore, in order to fully manipulate IC in order to maximize output, a company has to first find out the most influential factors affecting their operational performance. The empirical test results of this study prove that IC is one of the most critical elements in the digital content industry in terms of influencing operational performance. In addition, manpower and customer capital are the representative dimensions of IC.

Customer capital occupies a critical position in the digital content industry, which is primarily knowledge-based. Most of the core businesses in the digital content industry should focus on fostering good relationships with their customers so that they can fully understand their needs and thus promote customer satisfaction. Second, manpower capital has a critical effect on the digital content industry; the content of the commodity is the soul of the digital content industry, and creativity is the critical factor in the content. In order to ensure that a firm's products are different from those of its competitors, brainstorming amongst employees is important. The maintenance of customer relationships depends on the efforts of employees, revealing the importance of manpower capital in the digital content industry. Firms within the digital content industry should pay a great deal more attention to the development of human resources in order to promote the competitiveness of their companies.

5.3 Firms with a small amount of capital can attain optimal production efficiency

In short, we can categorize digital content firms according to the amount of capital they possess. There are eight sample firms which have less than 0.5 billion New Taiwan Dollars (NTD), and four of them are efficient. Six firms had between 0.5 and 1.0 billion NTD in capital, and half of them proved to be efficient. Seven firms had more than 1 billion NTD in capital, and three of them proved to be efficient. Therefore, according to the research results of this study, it can be concluded that firms which have a small amount of capital can still attain optimal efficiency, from the perspective of IC. In other words, companies which only have a small amount of capital should accumulate their IC and thus acquire competitive advantages. Administrators in the digital content industry should also be strategic and forward thinking when making decisions, and should not only concern themselves with the quality and quantity of IC, but should also allocate resources to the right places in order to prevent the overinvestment and misplacement of resources. Thus, firms with a small amount of capital can optimize their efficiency and achieve optimal economic value through the accurate manipulation of IC for the creation of optimal operational performance.

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