Data Envelopment Analysis for Evaluating Knowledge Acquisition and Creation

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Abstract. From a managerial perspective, a model to measure the performance of knowledge acquisition and creation in organizations has been created based on the Data Envelopment Analysis (DEA) methodology. An application in higher educational institutions (HEIs) is shown. The model is found suitable for this purpose and is able to give some important insights to managers on what areas and to what extent they should improve in order to become efficient.

Keywords: Data Envelopment Analysis (DEA), Performance measurement, Knowledge creation, Knowledge acquisition, Knowledge management.

1 Introduction

An efficient knowledge management is crucial for an organization to achieve sustainable competitive advantages. Knowledge acquisition and creation are two of the most important elements in knowledge management. Knowledge acquisition is the process where an organization imports knowledge and expertise from external sources. On the other hand, knowledge creation refers to the process where the workers generate new knowledge, ideas, solutions, products, and services.

In this paper, these two elements are assessed collectively based on the fact that the ultimate outcome of knowledge acquisition is the creation of new knowledge. Evaluating them together would give management an overall picture on both areas.

The goal and originality of this paper is to develop a measurement model based on the Data Envelopment Analysis (DEA) methodology to evaluate these two elements in organizations. Some basic concepts of DEA are reviewed next. An explanation of the developed model follows. An actual application is then elucidated and discussed. Finally, conclusions and future research directions are drawn based on the findings.

2 Original DEA Models

DEA is a mathematical model for measuring relative efficiencies of a group of homogenous Decision Making Units (DMUs). It minimizes subjective judgments and is capable of handling multiple inputs and outputs. Assuming that there are n DMUs,

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each with m inputs and s outputs, the relative efficiency score of a test DMU_0 is obtained using the following model [1]:

$$\text{Max } \varepsilon_0 = \frac{\sum_{r=1}^{s} u_r y_{r0}}{\sum_{i=1}^{m} v_i x_{i0}}$$

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

$$u_r, v_i > 0, \quad \forall r, i \tag{1}$$

where,

$r = 1$ to s,
$i = 1$ to m,
$j = 1$ to n,
y_{rj} = amount of output r produced by DMU_j,
x_{ij} = amount of input i consumed by DMU_j,
u_r = weight assigned to output y_r,
v_i = weight assigned to input x_i.

Fundamentally, for a test DMU_0, Model (1) compares the inputs and outputs among all DMUs and determines the optimum set of weights (u_r and v_i) which would give DMU_0 the highest possible efficiency score ε_0, while constraining the efficiency scores of all DMUs to be within 1. The model is run n times to determine the efficiency scores for all DMUs. $\varepsilon_0 = 1$ indicates that a particular DMU is efficient, while a value less than 1 means it is inefficient.

Model (1) can be converted into its dual form, Model (2), which is also known as the envelopment form in DEA [1]. For a guideline on how to transform Model (1) into Model (2), readers are referred to [2].

$$\text{Min } \theta_0$$

$$\text{s.t. } \sum_j \lambda_j x_{ij} - \theta_0 x_{i0} \leq 0, \quad \forall i$$

$$\sum_j \lambda_j y_{rj} - y_{r0} \geq 0, \quad \forall r$$

$$\lambda_j \geq 0 \tag{2}$$

Model (2) has a feasible solution of $0 < \theta \leq 1$ and the optimal solution of a test DMU_0 is $\theta_0 = 1$, $\lambda_0 = 1$, and $\lambda_j = 0$ ($j \neq 0$). In other words, an efficient DMU has a score of θ = 1; while inefficient DMUs have scores of $\theta < 1$. For each inefficient DMU, Model (2) identifies a set of corresponding efficient DMUs as benchmarks for improvement. The reference sets for inefficient DMUs are identified from the non-zero λ values. In addition, for an inefficient DMU, DEA proposes improvement targets either by reducing the inputs by multiplying with θ_0 while maintaining the output levels, or by increasing the outputs by multiplying with $1/\theta_0$ while maintaining the input levels.

Model (2) is generally preferred than Model (1) because it is less computational cumbersome. This can be reflected from the constraints of the models. The constraints of Model (1) are more complicated than those of Model (2). Furthermore, Model (2) is favored because it can identify reference sets for the DMUs as described above. It should be noted that both efficiency scores, ε_0 and θ_0, obtained from the two models are identical.

In short, the main function of DEA is as an analytical tool to assess and benchmark the performance of various DMUs.

3 Developed Model for Knowledge Acquisition and Creation Performance Measurement

DEA serves as a suitable tool to evaluate the performance of knowledge acquisition and creation in an organization by viewing it as a process that converts multiple inputs into multiple outputs. These input and output data are analyzed using a performance measurement model developed based on Model (2). The results of the analysis will be the performance scores of all DMUs and improvement targets for those inefficient ones. The conceptual framework of the evaluation model is illustrated in Fig. 1.

One important issue in performing an analysis using DEA is determining what input and output data to be used. Thus, a review on the past literature has been done. Tables 1 and 2 summarize the measures, their references, and descriptions. Note that the list is not meant to be distinctive and can be edited based on managerial opinions.

Next, to propose improvement targets for inefficient DMUs, the outputs are to be increased by multiplying with $1/\theta_0$, while the inputs remain unchanged. Reducing inputs is undesirable because knowledge workers, as an input, are one of the most valuable assets of an organization. The improvement targets are formulated as:

$$\hat{y}_r = y_r \times \frac{1}{\theta_0} \tag{3}$$

4 An Application

An application of the developed model will be demonstrated in higher educational institutions (HEIs). Higher education is a knowledge-intensive industry and thus it

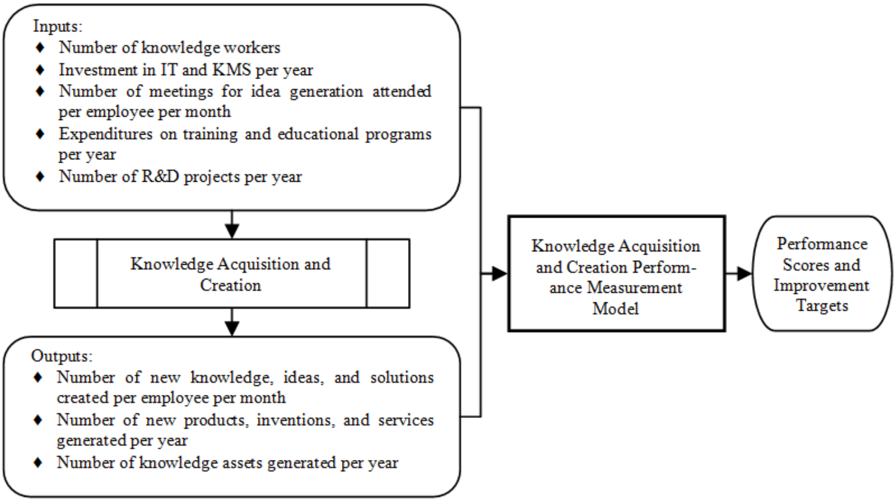

Fig. 1. Conceptual framework of knowledge acquisition and creation performance measurement model

Table 1. Input measures

Measures and References	Descriptions
x_1: Number of knowledge workers [3-9]	Knowledge workers are one of the fundamental elements of knowledge acquisition and creation. They acquire and generate new knowledge, ideas and solutions. A worker's mind itself is a developer and reservoir of tacit knowledge. They solve problems and make important decisions to improve the organizational performance.
x_2: Investment in IT and KMS per year [4-5], [8-11]	Information technology (IT) and knowledge management system (KMS) are the two basic architectures of knowledge discovery. With these, workers can rapidly search, acquire, extract, and retrive knowledge. Moreover, IT and KMS support the collaborations and communications among the workers and enable the formation of virtual communities of practice (CoPs) both internally and externally which are important for knowledge acquisition and creation.
x_3: Number of meetings for idea generation attended per employee per month [3], [9], [12-15]	Examples of idea generation meetings are brainstorming and strategic meetings. In such meetings, new knowledge and ideas would be sparked and generated through interactions and discussions among the workers.
x_4: Expenditures on training and educational programs per year [3-11], [13-14]	Ongoing training and educational programs are means to transfer up-to-date knowledge to the workers. External trainers can also be hired to give training sessions on special knowledge. This has proven to be an effective way of acquiring external knowledge and diffusing it to the target audiences. After the workers have acquired new knowledge, their personal knowledge bases are enhanced and more new ideas and knowledge can be generated.
x_5: Number of R&D projects per year [4-5], [9], [16]	An organization's success is greatly influenced by its innovations. R&D projects are necessary for an organization to create new products, inventions and services. The number of R&D projects serves as a proxy measure for the level of effort of an organization in developing new knowledge.

Table 2. Output measures

Measures and References	Descriptions
y_1: Number of new knowledge, ideas, and solutions created per employee per month [3], [6-7], [15]	New knowledge, ideas, and solutions are created by the knowledge workers via the process of knowledge creation. In addition, by acquiring knowledge externally, new knowledge, ideas and solutions may be imported into a company as well.
y_2: Number of new products, inventions, and services generated per year [3-6], [8-9]	New products, inventions, and services can be generated via knowledge acquisition and creation. Particularly, the outcomes of R&D projects are new products and services which can improve an organization's competitiveness and increase its market share.
y_3: Number of knowledge assets generated per year [3-9], [16]	Another output of knowledge acquisition and creation is the generation of knowledge assets such as patents, copyrights and scientific publications. By leveraging its knowledge assets, an organization can achieve sustainable competitiveness.

serves as a perfect test subject for the model. This section explains the implementation of the model to assess HEIs' knowledge acquisition and creation performance.

A survey was conducted using a specially designed questionnaire to collect the data needed. It was conducted through mails within Malaysia. Firstly, the recipients were sampled from the Malaysian Ministry of Higher Education's online database. Next, the questionnaire was sent to potential respondents along with an explanation cover letter. The respondents chosen were presumably in a position to comment on their institutions' knowledge management and have access to the information needed.

At the end of the survey, 23 usable responses were obtained. In this study, the data were used to compute relative efficiencies of the HEIs. Response rate does not have effects on the results' accuracy, and thus it is not a concern as long as the responses are sufficient for the analysis.

A MATLAB program was written based on the developed model. The data were analyzed using the program to obtain the performance score of each HEI. Results are summarized in Tables 3 and 4. Table 3 shows the performance score and ranking along with the reference set for each DMU. Table 4 presents the improvement targets for the inefficient DMUs.

DMUs with a score of 1 are efficient, while those score less than 1 are considered inefficient. From Table 3, it can be observed that performance scores of the DMUs range from 0.1501 to 1, with an average score of 0.6431. Out of 23 DMUs, 7 are efficient and 16 are inefficient. As additional information, the third column shows the ranking of the DMUs based on their scores. From this piece of information, the organizations can know where they are positioned relatively to their competitors in the same industry and take it as a motivation to improve their performance.

Also recorded in Table 3 are the corresponding λ values of the reference sets. The greater the λ value means the referred DMU is closer to the DMU under evaluation in terms of their input-output data. This information is useful for an organization to know which efficient DMUs it is being benchmarked with, so that it can improve itself by learning from them. For example, DMU_3's performance score is 0.64, and from Table 3, its manager can know that the efficient DMUs it is being benchmarked with are DMU_{16} and DMU_{22} with λ values of 0.69 and 1.25 respectively. By understanding the operations of these 2 DMUs, appropriate strategies can be devised to improve its knowledge acquisition and creation. Furthermore, the manager can choose to focus more on DMU_{22} because of its larger λ value.

Table 3. Performance scores and reference sets of DMUs

DMU	**Score**	**Rank**	**Reference Set**									
			DMU	λ	DMU	λ	DMU	λ	DMU	λ	DMU	λ
1	1.0000	1	1	1.00								
2	1.0000	1	2	1.00								
3	0.6400	11	16	0.69	22	1.25						
4	0.3345	20	5	0.02	22	0.49						
5	1.0000	1	5	1.00								
6	0.5054	13	2	0.01	5	0.01	13	0.38	22	1.29		
7	0.8157	10	1	0.11	13	1.27	22	0.09				
8	0.2545	21	13	0.01	16	0.47						
9	0.8341	9	13	0.27	16	0.47						
10	0.2400	22	13	0.24	16	0.10	22	1.99				
11	1.0000	1	11	1.00								
12	0.5555	12	2	0.12	11	0.01	13	0.51				
13	1.0000	1	13	1.00								
14	0.3604	19	2	0.01	11	0.01	13	0.28	22	0.35		
15	0.1501	23	13	0.98	16	0.22	22	0.64				
16	1.0000	1	16	1.00								
17	0.8889	8	16	0.25								
18	0.4308	17	5	0.01	13	0.05	16	0.54	22	0.32		
19	0.4630	15	2	0.02	11	0.02	13	0.10	16	0.10	22	0.47
20	0.4551	16	1	0.01	16	0.18						
21	0.4895	14	5	0.01	13	0.01	22	1.49				
22	1.0000	1	22	1.00								
23	0.3735	18	1	0.35	13	0.95	22	0.60				

Improvement targets were determined for every inefficient DMU as recorded in Table 4. These targets can be used by an institution as a guideline for future improvements. Take DMU_7 as an example, its performance score is 0.8157, thus the output levels have to be improved by 22.6% (1/0.8157 = 1.226). Its improvement targets are therefore $\hat{y}_1 = 8$, $\hat{y}_2 = 24$, and $\hat{y}_3 = 323$. In order for DMU_7 to be efficient, it has to increase these measures respectively while maintaining the same input levels. With this information on hand, the manager can then decide on how to channel the resources into specific improvement initiatives.

Table 4. Improvement targets for inefficient DMUs

DMU	Improvement Targets		
	$\hat{y}_1$	$\hat{y}_2$	$\hat{y}_3$
3	55	18	8
4	15	3	30
6	40	26	111
7	8	24	323
8	12	8	8
9	4	4	70
10	63	21	63
12	2	64	182
14	12	14	14
15	27	54	200
17	3	3	3
18	24	12	24
19	18	22	11
20	3	9	3
21	45	5	21
23	27	27	268

5 Conclusions

This paper has presented a performance measurement model for knowledge acquisition and creation using DEA. It proves to be a suitable model to evaluate these aspects effectively and conveniently. The information obtained from the developed model could help organizations to identify the inefficient areas and improvement targets in order to become efficient. These can be done by referring to their corresponding efficient benchmarked DMUs and the improvement targets.

The model has been tested in HEIs, which represent a highly knowledge-based industry. However, since knowledge acquisition practices may vary from one industry to another, it is necessary to test the model in other industries. In addition, though the measures proposed in this paper are as generic as possible to ease their future applications in other areas, they should be reevaluated based on different industries and modified wherever necessary.

Another element that can be included in future studies is finding the best practices and critical success factors of knowledge acquisition and creation in one industry. By collecting additional information such as what techniques and practices that organizations have implemented and upon obtaining their performance scores, it should shed some lights on which of the techniques and practices are indeed leading the organizations toward effectiveness and sustainable competitive advantages.

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