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Selection of Guided Surgery Dental Implant Systems Using Network Data Envelopment Analysis

I-Fei Chen[1]
***Chien-Chih Wang[2]**
Shui-Lien Chen[1]
Yu-Chin Kao[1]

[1]Dept. of Management Sciences, Tamkang University, Taiwan
[2] Department of Industrial Engineering and Management, Ming Chi University of Technology, Taiwan

All dental implant system suppliers typically claim the advantages and superiority of their product's specific attributes and functions. However, as assessment criteria are often inconsistent and conflicting, clinical dentists find it difficult to choose the most appropriate dental implant system. The present study used two-stage data envelopment analysis to measure the overall efficiency of individual dental implant systems and the relative efficiency of each phase of the selection process. The results of the present study can not only provide decision-making information for users, such as medical organizations, dentists, and patients, but may also inform guidelines for system producers to improve dental implant performance.

Keywords: Frontier projection, two-stage DEA, supplier selection, dental implant system

The introduction of computed tomography (CT) and development of the 3-dimensional implant planning software technology, CAD/CAM (computer-aided design/computer-assisted manufacturing), are undoubtedly important achievements in the field of dental implants (Wagner et al., 2001; Marchack, 2007; Chen et al., 2010). A thorough diagnosis, careful arrangement of implant position before surgery, and accurate implantation are critical for a predictable healing effect. Image-guided navigation surgery or stereographic surgical guidance using CAD-CAM technique is developed for this purpose. Currently, many software programs and hardware designed by different companies are available. (Ewers et al., 2004; Azari and Nikzad, 2008; Neugebauer et al., 2010).

Although dynamic systems were reported to provide more accurate guidance to users (Jung et al., 2009), they may cause more errors than static systems (Widmann, and Bale, 2006; Vercruyssen et al., 2008; Neugebauer et al., 2010). Today, there appears to be a trend toward static template - based guidance

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*Corresponding author: ieccwang@mail.mcut.edu.tw

systems in dental implantology. To address the above mentioned conflict that higher accuracy dynamic systems do not ensure higher acceptance by users, manufacturers of systems should address " accuracy" from a production perspective and " acceptance" from a market perspective to ensure their survival and success. If the performances of different systems are assessed solely based on accuracy, a prejudiced outcome will be obtained. Thus, the present study attempted to balance these two aspects of performance-assessing criteria by employing two-stage data envelopment analysis (DEA). The first stage is referred to as the production-oriented phase and focuses on accuracy efficiency, while the second stage is referred to as the market-oriented phase and focuses on acceptance efficiency. The overall efficiency of this network model suggests the priority of system selection and also indicates potential improvements for manufacturers.

DEA is a linear programming technique used to evaluate the efficiency of decision-making units (DMUs) on the basis of multiple inputs and outputs (Butler and Li, 2005). As the input and output pre-assigned weights are derived from a mathematical model, without presumption on characterizing input and output variables, the results of DEAs are impartial and are immune from manipulation by subjective factors. However, the original DEA was unable to present important transformation and relationships between any two stages in a process while considering DMU as a " black box" (Sexton and Lewis, 2003; Cao and Yang, 2011). Conversely, Cook et al. (2010) posited that a network structure with intermediate measures is required, where outputs from the first stage become the inputs into the next stage in a process (Premachandra et al., 2012). One of the most studied and applied DEA network structures is a two-stage process (structure) where DMUs use inputs in the first stage to produce outputs (Chen and Zhu, 2017). Derived from the main concepts of multiple stage DEA, several DEA-based approaches have been used to examine supplier– buyer supply chain (or two-stage process) settings. (Cooper et al., 2011)

In dentistry, the selection of a CAD-CAM implant system is an application of supply chain management. The two-stage DEA model readily lends itself to the evaluation of the overall performances of system candidates and induces managerial implications on individual phases of process (Chen et al., 2010). In the present study, we aimed to determine an overall efficiency score for the entire process and calculate an efficiency score for each of the individual stages by means of employing the two-stage DEA model. Based

on frontier projection and peer benchmarking, the present study can provide system manufacturers with a clear indication of the strengths and weaknesses of both production and market acceptance stages.

The present manuscript is presented in five sections. The rest of the sections are organized as follows. Section 2 gives an overview of two-stage DEA and DEA in medical applications. Section 3 delineates the present research methodology. Section 4 presents an empirical study and associated results. Conclusions and recommendations for further research are made in the Section 5.

LITERATURE REVIEW

- Surgical Implant Dentistry

According to the 2005 survey of the Bureau of National Health Insurance in the Department of Health in Taiwan, only 56.5% of citizens between 12 and 64 years of age had 28 teeth, whereas the rest had false or missing teeth and dental implants. The average number of lost teeth was 3.5, with only 20% of people aged >65 years having all 28 original teeth. In this population, the average number of lost teeth was 14.8. Meanwhile, the average number of lost teeth among citizens aged 12 was 5.6 (Tsai, 2009).

Dental implantation has a history of over 50 years since 1960. From the very beginning, this approach has focused on implant fixtures that can achieve osseointegration. To date, the approach aims to shorten the time to osseointegration while demanding that the implant position matches with the future filling material on the surface and integrates well with gums, alveolar bone, and surrounding teeth to ensure the need for beauty and function. To achieve the above mentioned demands, the location, angle, and direction of implant fixtures are critical (Kopp, 2003; Vercruyssen et al., 2008).

The development of computer-assisted surgical guidance and compute-navigated surgeries has shortened the osseointegration time, reduced treatment and waiting time, and allowed the performance of minimally invasive surgery with immediate recovery and little bleeding without the requirement for incisions or suturing (Valente et al., 2006). This approach can postoperatively reduce patient discomfort and allow precise treatment. The implant fixture can be placed in an ideal position that facilitates optimal fabrication of prostheses. Surgical damage to the surrounding anatomic structures, such as the maxillary sinus and nerves

of the mandibular alveolar bone, can be prevented. Thus, the safety of surgery is enhanced (Schneider et al., 2006; Kero, et al., 2010).

When used as implant positioning devices, computer-assisted guidance systems can be categorized into "static" and "dynamic" systems (Jabero and Sarment; 2006; Schneider et al., 2006; Neugebauer et al., 2010).

- Dynamic system: computer-assisted surgical navigation, which adopts a navigation system to assist dental implant surgery, was first used in stereotactic neurosurgery and then adopted by other medical areas. It can discern the location of pathological changes and anatomic structures. During the process of dental implantation, the navigation equipment is set by the dental chair (Ewers et al., 2004; Ewers et al., 2005). Before surgery, the dentist can perform spatial registration by using the specific anchor point for arrangement on the navigation system. During surgery, CT scanning images are connected with patient images so the process of dental implantation can be seen on the screen. The relative position and angle of the simulated implant and the drill bit during ongoing drilling can be simultaneously observed. Important organs can be marked by special software to enhance patient safety. Last, the dentist can insert the implant precisely into jawbone. The navigation system also allows the dentist to change plans and adjust the implant to a more suitable position according to clinical experience (Widmann et al., 2005; Widmann and Bale, 2006; Casap et al., 2008).
- Static system: computer-assisted surgical guidance can be divided into two types according to the means of production.

Stereolithography (STL) Surgical Template:

The patient has to wear a suitable image guide and undergoes CT scanning. The DICOM file is recombined as a 3D image with the patient model of jawbone or simulated surgical guidance by rapid prototyping (Sohmura et al., 2009). Rapid prototyping is based on non-traditional methods. The computer-assisted design software helps to produce a 3D image. This image is transformed into STL file, and the STL file is uploaded to the rapid prototyping system, which can divide the scopes according to the user and create a model, layer by layer.

Rapid prototyping machine development has gradually attracted the attention of scholars and industries, predominantly as these machines can reduce the surgery duration. Further, this system can be easily adopted and is suitable for various products. This type of template adopts a guide tube for drill bit guidance (Fortin et al., 2002; Fortin et al., 2004). Clinically, a guide tube with a comparable diameter to the drill bit is adopted to limit the drill bit direction. A template can have several guide tubes with different diameters for replacement and can also create several templates with different guide tubes of differing diameter for the replacement of drill bit to improve guidance (Sarment et al., 2003).

This method is more convenient than navigation before surgery and more similar to the traditional process of dental implantation. Further, this approach is commonly adopted because it is easily understood and accepted by dentists.

Computer-Driven Drilling Surgical Template:

Patients have to wear special image navigating templates before undergoing CT scanning. Then, a DICOM file is recombined and planed by professional software. The special navigation device on the image navigation template is used for spatial navigation and the planed implant is transferred to the drill bit and drilling system (Chen, 2010). On the patient's plaster cast, drilling is initiated in accordance with the planned position. Last, the guide tube is added and the template is completed. During surgery, the drill bit is guided by a relative guide tube of differing diameter (Klein and Abrams, 2001).

- Two-Stage DEA

In recent years, a myriad of DEA studies have focused on two-stage processes (Chen et al., 2010). In the past, traditional DEA was only able to estimate the relative efficiency of a sole step of the process for DMUs. Instead, this approach considers the production process of a DMU as a black box, which does not completely represent the reality of the efficiency of the various stages of the process of the DMU as part of a continuous set of activities. Therefore, two-stage DEA may allow assessment of the actual operational efficiency of the DMU. (Liu et al., 2012; Lozano et al., 2012).

The two-stage DEA is a form of network DEA. The network DEA model originated by Färe and Grosskopf (1996) is built around the concept of sub-technologies within the "black box" of DEA. Färe and Grosskopf deem the production process as a network, which includes three parts: inputs, outputs, and intermediate

products. Furthermore, intermediate products refer to the concept of transformation from input to output. This concept can be used to provide a complete DMU assessment through all aspects of the decomposition of the production process. (Cooper et al., 2011).

Seiford and Zhu's (1999) initiatively applied two-stage DEA for evaluating US commercial bank operational performance in a two-stage process, characterized by profitability and marketability. In their study, profitability was measured in the first stage using labor and assets as inputs and profits and revenues as outputs. In the second stage for marketability, the profits and revenue were then used as inputs, while market value, returns, and earnings per share constituted the outputs. Chilingerian and Sherman (2004) described a two-stage process in measuring physician care. Their first stage is a manager-controlled process with inputs including registered nurses, medical supplies, and capital and fixed costs. These inputs generate the outputs or intermediate measures, including patient days, treatment quality, and drugs dispensed among others. The outputs of the second physician-controlled stage include research grants, patient status, and quantity of individuals trained according to specialty. Abad et al. (2004) took advantage of two-stage DEA to profile 30 stocks in the Spanish manufacturing industry between 1991 and 1996.

Recently, numerous applications of two-stage DEA have extended into a variety of industries and research communities. For example, Fukuyama and Weber (2010) used a slacks-based inefficiency measure for a two-stage system with bad outputs to estimate the performance of Japanese banks. Andrew and Leon (2011) used the two-stage DEA to determine the efficiency of warehousing industry. Zha et al. (2012) used a two-stage DEA model with feedback developed to evaluate team performance, efficiencies of the operating environment, team members, and their impacts on overall efficiency. Premachandra et al. (2012) proposed a novel two-stage DEA model that decomposes the overall efficiency of a DMU into two components and demonstrated its applicability by assessing the relative performance of 66 large mutual fund families in the US over the period 1993–2008.

In summary, two-stage DEA can provide useful insights for solving managerial problems in the real world. This approach is applicable in a variety of industries and interdisciplinary issues, including medical supplier selection, the main topic of the present study.

- DEA in Medical Applications

DEA has been developed as a powerful quantitative and analytical tool for evaluating the efficiency over 30 years. After the initial study of Cooper and Rhodes was published, this trend has continued (Cooper et al., 2011). There are numerous scholars who devise new DEA models to improve the evaluation of efficiency, and DEA has matured and become widely adopted (Liu et al., 2012). DEA was introduced to the health-care industry in 1986 (Banker et al., 1986). Banker et al. (1986) evaluated world-wide medical service and the efficiency of medical organizations based on multiple qualitative and quantitative measurements.

In recent times, DEA application to world-wide medical services remains fruitful and promising. Huang (1989) used a CCR model to perform a multidisciplinary evaluation of different organizational approaches to rural primary health-care delivery from 1978 to 1983. DEA has been used by heterogeneous organizations for cost accounting, production, and regression analysis. In Northern Ireland, Mckillop et al. (1999) estimated the technical, scale, and size efficiency of acute hospitals over 1986–1992, concluding to expand larger hospitals and restructuring/closing smaller hospitals, and indicating that the expansion of large hospitals may not yield substantial efficiency gains. Puig-Junoy (2000) used CCR, BCC, and Assurance Region (AR) approach to evaluate the efficiency of 94 acute care hospitals in Spain and explored the influence of hospital environment on efficiency. This study adopted a two-stage approach of DEA and a regression model to analyze the production and cost frontier of 94 acute care hospitals. This paper used a homogeneous method of partitioning cost efficiency into the DEA and efficiency measurement literature by adding results.

The efficiency and productivity of the hospitals in an Austrian province from 1994 to 1996 were studied by Maria (2002). Maria used two models and obtained differing results. An average efficiency of 96% by the first model with conservative output measurement and that of 70% from the other model with credit points was calculated. From 1994 to 1996, the average efficiency in the first model was stable; however, in the other model, efficiency regularly increased. Thus, efficiency change over time differently develops and needs to be screened for (Hofmarcher, et al., 2002). Brenda (2005) adopted DEA and Stochastic Frontier Analysis (SFA) to assess the efficiency of acute public hospitals in Ireland between 1995 and 2000. This study was the first to estimate the average efficiency of hospitals in Ireland and emphasize the variation in technical efficiency among hospitals. Wei et al. (2011) adopted cross-sectional and longitudinal efficiency analysis models to analyze the operational efficiency of medical centers. They further constructed managerial decision-making

path models and analyzed the level of hospitals in various managerial decision-making path models and identified paths to be improved in Taiwan.

The above mentioned-references indicate that DEA is mostly used by medical services for the evaluation of efficiency of medical organizations (sun and Luo, 2017; Barouni, 2016). There are few studies that have adopted DEA in assessing medical facility performance.

- The Technology Acceptance Model

The technology acceptance model (TAM) was proposed by Davis (1989). A subsequent study by Davis et al. (1989) was based on the theory of reasoned action (TRA) (Fishbein and Ajzen, 1975), which as an instrument used to predict the likelihood of a new technology being adopted within a group or an organization (Turner et al., 2010).

TAM is founded upon the hypothesis that technology acceptance and use can be explained in terms of user's internal beliefs, attitudes, and intentions, and found that it could better explain user's acceptance of information technology. Two important concepts of TAM are perceived usefulness and perceived ease of use (Davis, 1989). Perceived usefulness means that the subjective recognition of the user on certain information systems can enhance the efficiency of work. Perceived ease of use refers to the time required for a user to familiarize themselves with a certain system. Figure 1 illustrates the TAM model.

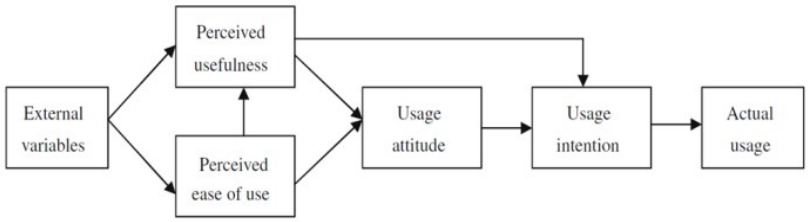

Figure 1. The Technology Acceptance Model

Numerous empirical studies have found TAM to be a robust and parsimonious model for the explanation of technology usage (Lee et al., 2003) in areas including m-commerce (Pavlou, 2003; Bruner and Kumar, 2005), email, banking technology, online games, and enterprise resources planning (ERP) systems (Gefen, Karahanna, & Straub,2003). TAM has also been applied in health care and conducted in a wide variety of

countries. Several studies have been conducted in the UK (Van Schaik et al., 2002; Barker et al., 2003), the mainland US (Liu & Ma, 2005), Australia (Schaper and Pervan, 2007), and Taiwan (Tung et al., 2008).

The present study applied the concept of the TAM to construct a system selection preference matrix and aimed to provide users with an important basis for selecting or evaluating systems.

METHODOLOGY

- Frontier Projection Two-Stage DEA

Chen et al. (2010) posited that the previous two-stage models in literature were unable to provide an efficiency frontier or the correct relative efficiency for every DMU because they do not address potential conflicting roles of intermediate measures between the two stages. Further, the second stage may have to reduce its inputs (intermediate measures) to achieve an efficient status; however, this would imply reduction in the first stage outputs, thereby reducing the efficiency of that stage. A number of DEA studies have been performed in an attempt to address this type of conflict (Liang et al., 2008). A number of authors, including Chen and Zhu (2004) and Chen et al. (2006) have presented a linear DEA type model where the intermediate measures are set as decision variables. However, their individual stage efficiency scores do not provide information on the overall performance and best-practice of the two-stage process. Similarly, the model of Kao and Hwang (2008), via adjusting the inputs and outputs by the efficiency scores in a two-stage process, is generally insufficient to yield a frontier projection.

Chen et al. (2010) developed a two-stage model based upon the assumption of constant returns to scale (CRS). A generic two-stage process, as shown in Fig. 3-1, can be applied to each of a set of n DMUs. If each DMU_j (j = 1, 2,..., n) is assumed to have m inputs x_{ij} (i = 1, 2,..., m) to the first stage, and D outputs z_{dj} (d = 1, 2,..., D) from that stage, these D outputs then become the inputs to the second stage, and therefore, behave as intermediate measures. The outputs from the second stage are y_{rj} (r = 1, 2,..., s).

For DMU_j, the study denotes the efficiency ratios for the first stage as θ_j^1 and the second as θ_j^2. Below are the definitions of θ_j^1 and θ_j^2

$$\theta_j^1 = \frac{\sum_{d-1}^{D} w_d z_{dj}}{\sum_{i=1}^{m} v_i x_{ij}} \text{ and } \theta_j^2 = \frac{\sum_{r-1}^{s} u_r y_{rj}}{\sum_{d=1}^{D} \tilde{w}_d z_{dj}}$$

Where $v_i, w_d, \tilde{w}_d$ and u_r are unknown non-negative weights , $w_d = \tilde{w}_d$

The two-stage overall efficiency ratio is defined as $\theta_j^1 \cdot \theta_j^2$ which is equal to $\theta_j = \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}}$.

Input-Oriented Model

For each DMU$_0$, Chen et al. (2010) introduce $\tilde{z}_{d0}$ $(d = 1, \ldots D)$, representing a set of new intermediate measures to be determined, then break the constraints $\sum_{j=1}^{n} (\lambda_j - \mu_j) z_{dj} \geq 0$ into two new sets of constraints as the below, to revise the model by Kao and Hwang (2008).

$$\sum_{j=1}^{n} \lambda_i z_{dj} \geq \tilde{z}_{d0}, \qquad d = 1,2,\ldots,D,$$

$$\sum_{j=1}^{n} \mu_i z_{dj} \geq \tilde{Z}_{d0}, \qquad d - 1,2,\ldots,D,$$

$$\lambda_i, \mu_i \geq 0, \qquad i = 1,2,\ldots,m$$

The first new set of constraints treats the $\tilde{z}_{d0}$ as "outputs". and the second set treats the $\tilde{z}_{d0}$ as "inputs". They propose the DEA type model as

Min $\tilde{\theta}$

s.t.

$$\sum_{j=1}^{n} \lambda_i x_{ij} \leq \tilde{\theta} x_{i0}, \qquad i = 1,\ldots,m,$$

$$\sum_{j-1}^{n} \mu_j y_{rj} \geq y_{r0}, \qquad r = 1,\ldots,s,$$

$$\sum_{j=1}^{n} \lambda_i z_{dj} \geq \tilde{z}_{d0}, \qquad d = 1,\ldots,D,$$

$$\sum_{j=1}^{n} \mu_i z_{dj} \leq \tilde{z}_{d0}, \qquad d = 1,\ldots,D,$$

$$\tilde{z}_{d0} \geq 0, \; d = 1,\ldots,D,$$

$$\lambda_i \geq 0 \ , \qquad j = 1, \dots, n,$$

$$\mu_i \geq 0 \ , \qquad j = 1, \dots, n,$$

$$\tilde{\theta} < 1. \quad (1)$$

The dual can be expressed as:

$$\text{Max} \quad \sum_{r=1}^{s} u_r y_{r0}$$

$$s.t. \quad \sum_{r=1}^{s} u_r y_{rj} - \sum_{d=1}^{D} w_d^2 z_{dj} \leq 0, \qquad j = 1,2, \dots, n,$$

$$\sum_{d-1}^{D} w_d^1 z_{dj} - \sum_{i-1}^{m} v_i x_{ij} \leq 0, \qquad j = 1,2, \dots, n,$$

$$\sum_{i=1}^{m} v_i x_{i0} = 1$$

$$W_d^2 - W_d^1 \leq 0, \qquad d = 1,2, \dots, D$$

$$W_d^1, W_d^2 \geq 0, \ d = 1,2, \dots, D; \ v_i \geq, i = 1,2, \dots, m; \ u_r \geq, r = 1,2, \dots, s \quad (2)$$

Output-Oriented Model

A general model of the output-oriented version is given by

$$\text{Min} \ \frac{\sum_{i=1}^{m} v_i x_{ij0}}{\sum_{r=1}^{s} u_r y_{rj0}}$$

$$\text{s.t.} \ \theta_j^1 < 1 \text{ and } \theta_j^2 \leq 1 \text{ for all } j,$$

For each DMU_0, the relative efficiency can be derived by the below optimization model which specifies as

$$\text{Min} \sum_{i=1}^{m} v_i x_{i0}$$

$$\text{s.t.} \ \sum_{r-1}^{s} u_r y_{rj} - \sum_{d-1}^{D} W_d Z_{dj} \leq 0, \qquad j = 1,2, \dots, n,$$

$$\sum_{d=1}^{D} w_d z_{dj} - \sum_{i=1}^{m} v_i x_{ij} < 0\,, \qquad j = 1,2,\dots,n,$$

$$\sum_{r=1}^{s} u_r y_{r0} = 1,$$

$$\sum_{j=1}^{n} \lambda_i z_{dj} \geq \tilde{z}_{d0}\,, \qquad d = 1,\dots,D,$$

$$\sum_{j=1}^{n} \mu_i z_{dj} \leq \tilde{z}_{d0}\,, \qquad d = 1,\dots,D,$$

$$W_d, d = 1,2,\dots,D;\ v_i, i = 1,2,\dots,m;\ u_r, r = 1,2,\dots,s\ \geq 0. \qquad (3)$$

The dual can be expressed as:

Max $\tilde{\emptyset}$

$$\text{s.t.} \sum_{j=1}^{n} \lambda_i x_{ij} \leq x_{i0}\,, \quad i = 1,\dots,m$$

$$\sum_{j=1}^{n} \mu_j y_{rj} > \tilde{\emptyset}\, y_{r0}\,, \qquad r = 1,\dots,s,$$

$$\sum_{j=1}^{n} \lambda_i z_{dj} \geq \tilde{z}_{d0}\,, \qquad d = 1,\dots,D,$$

$$\sum_{j=1}^{n} \mu_i z_{dj} \geq \tilde{z}_{d0}\,, \qquad d - 1,\dots,D,$$

$$\tilde{z}_{d0} \geq 0, \quad d = 1,\dots,D,$$

$$\lambda_i \geq 0\,, \qquad j = 1,\dots,n,$$

$$\mu_i \geq 0\,, \qquad j = 1,\dots,n,$$

$\emptyset \geq 1$ (4)

From models (2) and (4), it can be seen that a set of optimal intermediate measures (z), individual stage, and overall efficiency scores are obtained.

In the dental implant system selection setting, factors such as ease of intraoperative handling and relative inexpensiveness are determinants of clinician willing to choose a system and an indication of market acceptance, which is also a major concern of system manufacturers regarding competitive advantage. Therefore, an output-oriented model was applied in the present study.

- Determination of Inputs, Intermediate Measures and Outputs

The assessment was divided into two stages: perceived usefulness and clinician acceptance. The former focused on the relative efficiency of accuracy of peer equipment, while the later focused on that of the acceptance of systems used by clinical dentists (Figure 2).

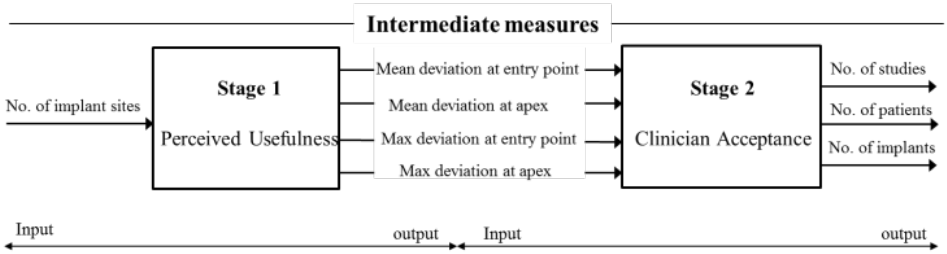

Figure 2. Dental System Selection Process

- Definition of Input in Stage 1

As the system accuracy reported by Jung et al. (2009) is a result of a meta-analysis derived from the number of implant sites, it is likely to be influential as an input factor in stage 1.

The number of implant sites refers to the amount of implant placements or drill holes in models, cadavers, and humans. The operational definition of the number of implant sites is the sum of the sites of systems in the reference article.

- Definitions of Intermediate Measures

The dental implant is an important choice of treatments for edentulous as well as partially edentulous patients as a definitive treatment. In patients not considered to be in a good condition for surgery or in whom anatomical treatment is likely to be challenging, precise implant surgery is absolutely necessary (Weitz et al., 2011). The position of the implant fixture is typically the key aspect of the entire implant surgery. Deviation of the implant may not only cause damaged perceptional nerves but also permanent abnormal perception or paralysis (Vercruyssen et al., 2008). Hence, a precise scheme of treatment can reduce the occurrence of complications and shorten the time required for treatment and recovery (Serrano et al., 2008). Successful dental implant is based on both proper osseointegration and the optimal position of the implant to provide aesthetics and function (Kopp et al., 2003; Widmann et al., 2005). The accuracy of implant is a reverse estimate of the overall deviation from the commencement to the completion of the placement. Deviation may occur at any stage and worsen over time. Therefore, studies that analyze the accuracy variables of implant position focused on deviation at the entry point of the implant, at the apex of the implant, in height, and of the axis of the drill or implant, as illustrated in Figure 3 (Schneider et al., 2006 and Van Assche et al., 2012). Owing to the absence of deviation in height and angle [(3) and (4) in Figure 3] in Jung's report, only two variables, deviations at entry point and apex, were available and used as the undesired outputs of stage 1 of the DEA in the present study.

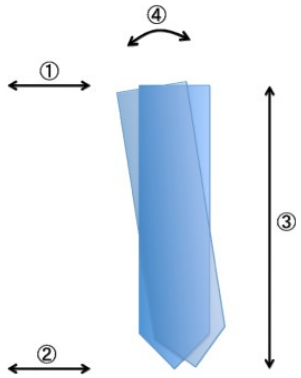

Figure 3. Operation Variables of Intermediate Measures

Direction of deviations in the variables of accuracy : (1) deviation at entry point, (2) deviation at apex, (3) deviation in height, and (4) angular deviation (Schneider et al., 2006).

Moreover, dentists are most concerned about the largest deviations that may occur in specific system. In dynamic or static systems, unacceptable and out of tolerance deviation may occur (Chen, 2010). From the viewpoint of patient security and laws, this type of deviation can be a serious risk once it has occurred. Thus, the largest deviation should be the major concern of dentists (Vercruyssen et al., 2008).

Therefore, the present study used four variables as outputs in stage 1 and inputs in stage 2 (i.e., intermediate measures). The definitions of these intermediate measures are as follows:

1. Mean deviation at entry point: Deviation error in a horizontal direction at the entry point of the drill or implant.
2. Mean deviation at apex: Deviation error in a horizontal direction at the apex of the drill or implant.
3. Max deviation at entry point: Deviation error in a horizontal direction at the entry point of the drill or implant causing the largest deviation via meta-regression analysis according to references.
4. Max deviation at apex: Deviation error in a horizontal direction at the apex of the drill or implant causing the largest deviation via meta-regression analysis according to references.

- Definitions of Outputs in Stage 2

1. The number of studies: The number of studies every system used in Jung's (2009) report on clinical outcome.
2. The number of patients: The number of patients every system used in Jung's (2009) report on clinical outcome.
3. The number of implants: The number of implants every system used in Jung's (2009) report on clinical outcome.

Logically, these three factors are indicators of clinician acceptance. Higher value in any of these variables indicates greater utilization of these systems in clinics. Market acceptance is the estimate goal of equipment vendors and users. Factors such as ease of intraoperative handling and relative inexpensiveness are determinants of clinician willing to choose a system, and also an indication of market acceptance, which is major concern of system manufacturers regarding competitive advantage. Therefore, the output-oriented model, which emphasizes output performance, was deemed appropriate for use in the present study.

RESULTS

We applied the data of Jung et al. (2009) to the software, DEAFrontier_OpeanSolver.xlam, developed in 2012 by Joe Zhu to conduct an empirical analysis.

The missing values for the mean apex and max apex of DMU6 were replaced with the meta-mean of dynamic principle members. The result is shown in Table 1.

DMU No.	DMU Name	No. of sites	Mean entry	Mean apex	Max entry	Max apex	No. of studies	No. of patients	No. of implants
Static Principle									
1	Nobel	28	0.89	0.99	1.16	1.26	2	57	347
2	Simplant	121	1.26	1.97	1.74	2.97	1	5	32
Dynamic Principle									
3	Treon	224	0.9	0.6	1.49	0.73	3	53	198
4	Robodent	15	0.35	0.47	0.44	0.56	1	20	71
5	Visit	99	0.72	0.99	0.91	1.37	2	28	122
6	Vector Vision	240	0.95	0.68	0.98	0.8	2	23	82
Mean		121.1667	0.8450	0.95	1.12	1.2817	1.8333	31	142
Median		110	0.8950	0.835	1.07	1.03	2	25.5	102

Table 1. The Original Data

As the outputs of stage 1 and inputs of stage 2 are undesirable deviations, we modified the DEA to overcome weaknesses in dealing with negative undesirable factors as follows: (Tseng, 2006)

1. To apply negative signs to undesirable factors to change to positive values and then adopt a DEA model to calculate efficiency.
2. To apply negative signs to undesirable factors and move the last number to change values to positive and then use a DEA model to calculate efficiency.
3. To take undesirable outputs as inputs and undesirable inputs as outputs.
4. To find the reciprocal of undesirable factors and deal with each in the DEA model.
5. To use the weak disposable model developed by Fare et. al. (1989) to evaluate the output loss.

In the present study, due to the characteristics of the data, it was deemed unreasonable to apply methods other than the reciprocal approach. The transformation of undesirable variables using the reciprocal approach is shown in Table 2.

DMU No.	DMU Name	No. of sites	Mean entry	Mean apex	Max entry	Max apex	No. of studies	No. of patients	No. of implants
Static Principle									
1	Nobel	28	1.1236	1.0101	0.8621	0.7937	2	57	347
2	Simplant	121	0.7937	0.5076	0.5747	0.3367	1	5	32
Dynamic Principle									
3	Treon	224	1.1111	1.6667	0.6711	1.3699	3	53	198
4	Robodent	15	2.8571	2.1277	2.2727	1.7857	1	20	71
5	Visit	99	1.3889	1.0101	1.0989	0.7299	2	28	122
6	Vector Vision	240	1.0526	1.4706	1.0204	1.2500	2	23	82
Mean		121.1667	1.3878	1.2988	1.0833	1.0443	1.8333	31	142
Median		110	1.1174	1.2403	0.9412	1.0218	2	25.5	102

Table 2. Transformed Data

Two-Stage Frontier Projection

We applied the transformed empirical dataset to the output-oriented two-stage model for frontier projection. Overall efficiency scores obtained from the output-oriented model can also be considered an expansion factor. Therefore, the relative efficiencies of DMUs are the reciprocal of expansion factors, which are summarized in Table 3.

As shown in Table 3, all 6 systems inefficiently performed in both networked stages, and no system had a perfect overall efficiency score of 1. The mean overall efficiency score and highest overall efficiency score were 0.1117 and 0.2543, respectively, for the Nobel system, which is a member of the Static principle. This score was followed by 0.2373 for Robodent and 0.0719 for Visit, members of the Dynamic principle. These results indicate substantial room for improvement in system efficiency. Among all the evaluated DMU, only Nobel and Robodent had above-average efficiency. Besides, Vector Vision and Simplant had efficiency scores of only 0.0297 and 0.0294.

DMU No.	DMU Name	Output-oriented scores	1/Output-oriented scores
Static Principle			
1	Nobel	3.9319	0.2543
2	Simplant	33.9830	0.0294
Dynamic Principle			
3	Treon	20.9702	0.0477
4	Robodent	4.2128	0.2374
5	Visit	13.9021	0.0719
6	Vector Vision	33.7021	0.0297
Mean		18.4504	0.1117
Median		17.4362	0.0598

* 1/Output-oriented scores = relative efficiency

Table 3. Output-Oriented Overall Efficiency Scores

Perceived Usefulness Efficiency and Clinician Acceptance Efficiency

After decomposing the overall scores, two efficiency scores were derived: perceived usefulness efficiency and clinician acceptance efficiency, respectively, referring to the first stage and second stage of this networked model (Table 4).

DMU No.	DMU Name	Perceived Usefulness		Clinician Acceptance	
		Scores	1/Scores	Scores	1/Scores
Static Principle					
1	Nobel	3.9319	0.2543	1.0000	1.0000
2	Simplant	33.8114	0.0296	1.0051	0.9949
Dynamic Principle					
3	Treon	19.0638	0.0525	1.1000	0.9091
4	Robodent	1.0000	1.0000	4.2128	0.2374
5	Visit	13.9021	0.0719	1.0000	1.0000
6	Vector Vision	23.1489	0.0432	1.4559	0.6869
Mean		15.8097	0.2419	1.6290	0.8047
Median		16.4830	0.0622	1.0525	0.9520

Table 4. Perceived Usefulness Efficiency and Clinician Acceptance Efficiency

Robodent from the dynamic principle had the highest efficiency in perceived usefulness, which indicates it was efficient at this stage. The second was Nobel from the static principle, whose efficiency was 0.2543. In this stage, only these two systems had efficiency above the average of 0.2419. In the stage of clinician acceptance, Nobel and Visit were found to be more easily accepted by doctors. Simplant had a high score of 0.9949. We found that Nobel and Simplant were static principle members. At this stage, the mean score of the static principle was higher than that of the dynamic principle.

In both perceived usefulness and clinician acceptance stages, we observed an interesting phenomenon. Robodent had the highest score in perceived usefulness but the lowest score of 0.2373 in clinician acceptance. In perceived usefulness, most systems of the dynamic principle had scores higher than the static principle. As each system has its own strengths and weaknesses in different dimensions involved with its sub-processes, the present study attempted to construct a system selection preference matrix to discover the merits of each system by comparing clinician acceptance to perceived usefulness. We employed the medians of these two dimensions (0.0622 and 0.9520, respectively) for perceived usefulness and clinician acceptance, to categorization systems into four quadrants; top-priority, customer-preferred, least-priority, technology-preferred (Figure 4).

In top-priority quadrants, there were two systems, Nobel and Visit, which performed well in both aspects of technology and usefulness. As systems in customer-preferred, for example Simplant, favor the easiness of use, the enhancement of accuracy should be considered to increase their competitiveness. In least-priority, Treon and Vector Vision were found to need enhancements in both acceptance and accuracy. Although Robodent, found to lie in the technology-preferred quadrant indicating high implant accuracy, had the highest score of efficiency in perceived usefulness, it overlooks the convenience of usage of clinical facilities.

According to the results of the present study, clinical doctors place greater emphasis on convenience of usage. Although dental implant suppliers place importance on accuracy, clinician doctors do not choose the most accurate system. Thus, we suggest that system suppliers should not only enhance accuracy on

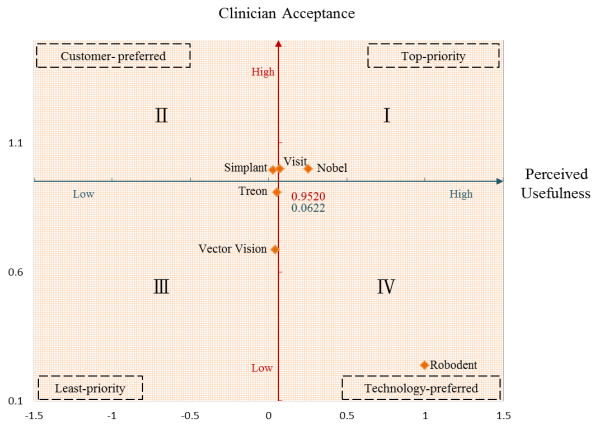

Figure 4. A System Selections Preference Matrix

technological wise but also consider the user's convenience. In this way, users can use the system with more precision and convenience of dental implantation. The causes of the above results are as follows:

- The experimental designs differed. During the experiments regarding accuracy, the deviations in human, model, and cadaver experiments were different. For example, the result from non-living experiments were better than that from clinical experiments. This may be attributable to studies on non-living tissues having a better viewpoint and angle and less interruptions by saliva or patient movement. Thus, the dynamic system has better accuracy that can lower the risks associated with dental implantation.

- The static system obviously has advantages because the arrangement of surgical guides is easy and the facilities are cheap. Besides, the dynamic system requires greater time before and during surgery. In particular, when patients make movements during surgery, general anesthetic is required to prevent these movements from affecting accuracy. This situation is not commonly accepted by doctors or patients during dental implantation.

Moreover, the present study provides system suppliers with the optimal values of intermediate measures, thereby allowing improvements in the overall efficiency of systems according to the suggested values (Table 5).

The two approaches of the computer navigated system have different strengths and weaknesses. Navigation provides surgeons with more freedom and flexibility to adjust the implant position, but it tends to create errors and is less accurate than the navigation system. It requires professional skills; therefore,

surgical knowledge, familiarity, and understanding of the doctor regarding the planned position of the implant influence the execution of system. Further, shaking hands may cause extra deviation. Regarding the static system, its advantages are convenience and ease of use. Therefore, these systems are more commonly

DMU No.	DMU Name	Mean entry	Mean apex	Max entry	Max apex
Static Principle					
1	Nobel	0.7073	0.7868	0.9219	1.0013
2	Simplant	0.6597	1.0314	0.9110	1.5550
Dynamic Principle					
3	Treon	0.8551	0.5701	1.4157	0.6936
4	Robodent	0.3500	0.4700	0.4400	0.5600
5	Visit	0.5805	0.7982	0.7337	1.1046
6	Vector Vision	0.8831	0.6321	0.9110	0.7437

Table 5. Optimal Intermediate Measures

used in studies of computer-guided oral implantology. However, dynamic system is required in certain cases and can be used in a wide range of craniomaxillofacial procedures (e.g., image-guided biopsies, removal of foreign bodies, arthroscopy of the temporomandibular joint, osteotomies, distraction osteogenesis, and tumor surgery) (Widmann and Bale, 2006).

CONCLUSION

The progress of surgery technology has ensured >95% success rate in dental implant surgery. In recent times, dental implantation has taken the place of traditional removable prostheses and has gradually become the dominant treatment due to its stability, greater function, and improved aesthetics after surgery. The dental implant market is increasingly thriving due to an aging population society; the retirement of baby boomers; and the low penetration rate of global dental implant treatments and aesthetic needs. Yet, careful arrangement of implant position prior to surgery, thereby allowing precise implantation, is critical in achieving predictably desirable treatment outcomes. CAD-CAM technology has been developed and quickly improved in this decade to fulfill these requirements.

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