The interdependencies of marketing capabilities and operations efficiency in hospitals

Foo Nin Ho[a],[*], Chin-wei Huang[b]

[a] Department of Marketing, San Francisco State University, 1600 Holloway Ave., San Francisco, CA 94132, United States
[b] Department of Business and Entrepreneurial Management, Kainan University, 1, Kainan Rd., Luchu, Taoyuan 338, Taiwan, ROC

ABSTRACT

Amid rising health care costs, health providers, and especially hospitals, are under pressure to provide quality medical care while controlling their operation costs. Hospitals face the challenge of balancing resource efficiency and delivering patient value. This mandates a close collaboration between marketing and operations, both of which are directly associated with the creation of patient value. This paper looks at the interdependencies of intangible marketing capabilities and operations in U.S. hospital performance. We employ a non-radial two-stage Data Envelopment Analysis (DEA) to measure and assess the interdependencies of intangible marketing capabilities (brand mind share) and operations in hospital performance. In addition, we test intangible marketing variables in a path analysis to determine their relationship with customer satisfaction and referrals. Our results show that intangible marketing assets are critical to the ability of hospitals to deliver patient value.

1. Introduction

Marketing plays an essential role in today's competitive environment (Porter, 2008). Good marketing results from careful planning and execution, including the use of state-of-the-art tools and techniques to maintain a sustainable competitive advantage (Kotler & Keller, 2007). Yet marketing productivity, defined as the efficiency and effectiveness of marketing strategies, can be difficult to achieve (Sheth & Sisodia, 2002) for numerous reasons, including: (1) inadequate attention to marketing productivity issues (ratio of output to input), (2) a reactive approach to marketing budgeting, and (3) lack of measurability in outputs. To help marketers deliver more value to customers at current or lower costs, researchers have started to measure marketing productivity in a more systematic and quantifiable way (Morgan, 2012; O'Sullivan & Abela, 2007; Rust, Ambler, Carpenter, Kumar, & Srivastava, 2004; Verhoef & Leeflang, 2009; Vorhies & Morgan, 2005). To achieve sustained competitive advantage (SCA), firms need to learn how to do the right thing (effectiveness) while doing things right (efficiency). The healthcare industry is a prime example of this challenge: Healthcare providers have to deliver quality health care while trying to control their costs to achieve SCA. As marketing has evolved in health care beyond the creative to become more analytic, hospitals can be better positioned to understand their market, their competition, and

their operational performance (Wolper, 2011, p. 327). This, in turn, will impact their customers, as well as the regulatory, technological, legal, and healthcare environments within which they must function. In addition, the increasing use of marketing performance benchmarks allows them to evaluate the effectiveness of their marketing efforts.

1.1. Resource-Based theory (RBT)

According to resource-based theory (RBT),[1] a SCA is derived from the efficient deployment of resources (inputs) in the development of inimitable capabilities to achieve certain objectives (outputs) through functional capabilities (Barney, 1991; Hitt, Xu, & Carnes, 2016). RBT assumes that SCA is achieved when resources are valuable, rare, imperfectly imitable, and when the firm has the ability to exploit resources (VRIO) (Barney & Hesterly, 2012; Nason & Wiklund, 2018) or core competence (Prahalad & Hamel, 1990). Both resources and capabilities play central roles in RBT (Kozlenkova, Samaha, & Palmatier, 2014). Resources are tangible and intangible assets controlled by the firm to implement strategies that may give rise to SCA (Barney & Arikan, 2005; Nath, Nachiappan, & Ramanathan, 2010). These resources generally fall under four categories: physical, financial, human, and organizational (Barney & Hesterly, 2012). Tangible assets include a firm's factories, its products, and distribution systems; its intangible assets

---

include its reputation among customers and teamwork among its managers.

Capabilities are a subset of a firm's tangible and intangible resources that allow it to take advantage of other resources within its control to improve their productivity (Makadok, 2001, p. 389). Amit and Schoemaker (1993, p. 35) define capabilities as "a firm's capacity to deploy resources, usually in combination, using organizational processes, to effect a desired end." While each firm may have the same access to external resources available for production, firms that can efficiently combine these resources to attain a certain objective have a competitive advantage over other firms. Vorhies and Morgan (2005, p. 82) identify eight distinct marketing capabilities that contribute to business performance: (1) product development, (2) pricing, (3) channel management, (4) marketing communications, (5) selling, (6) market information management, (7) marketing planning, and (8) marketing implementation. Their empirical analyses show the interdependencies among individual marketing capabilities in influencing firm performance, which includes customer satisfaction, market effectiveness, and profitability. Their results also show that marketing capabilities and firm performance can be identified and benchmarked.

Recent literature has highlighted how RBT can provide a theoretical framework for firms to build a SCA based on a combination of marketing capabilities and other internal resources (Barney, 2014; Morgan, Vorhies, & Mason, 2009; Wernerfelt, 2014) and stakeholders (Kull, Mena, & Korschun, 2016). The importance of this was highlighted by *Journal of Business Research*'s special issue on the topic of "Marketing Resources, Performance, and Competitive Advantage: A Review and Future Research Directions" (Davcik & Sharma, 2016). The market-based resources perspective increasingly focuses on the intangible and complementary resources on SCA and firm performance. Market-based resources include a subset of firm resources related to marketing activities, such as building brand equity, customer relationships, innovations, or knowledge (Barney, 2014; Wang & Sengupta, 2016; Wernerfelt, 2014). Srivastava, Shervani, and Fahey (1998) argue that intangible resources have greater effects than tangible resources on firm performance; coupled with organizational performance, as much as 70% of a firm's market value may be attributed to intangible resources (Capraro & Srivastava, 1997). Researchers have looked at marketing capabilities relative to technology (Dutta, Narasimhan, & Rajiv, 1999), new product development (Chen, Li, Evans, & Arnold, 2017), research and development (Calantone & Rubera, 2012), operations capabilities (Krasnikov & Jayachandran, 2008), manufacturing (Hausman, Montgomery, & Roth, 2002), among others. Studies have found that both marketing and operational efficiencies are key determinants of a firm's performance (Malhotra & Sharma, 2002; Nath et al., 2010) and customer value creation (Sawhney & Piper, 2002). A firm with strong marketing capabilities is able to use its understanding of customer needs to foster not only the development of new products and services but also such areas as customer satisfaction, brand equity, and customer loyalty.

1.2. Marketing capability metrics

Accounting remains the dominant metric for measuring marketing capabilities, as it offers a simple set of guidelines that practitioners can easily apply. For example, early work on marketing performance focused on using accounting measures such as sales, gross margins, and market share (Clark, 1999). The problem with using single accounting measures is that they are all post hoc indicators (Ambler, Kokkinaki, & Puntoni, 2004). Vorhies and Morgan (2005) have empirically shown the importance of marketing capabilities in influencing firm performance, as well as the ability to benchmark the relationship between the two. Other researchers have started to advocate for the importance of intangible marketing assets, such as brand equity (Aaker, 1996; Rust, Lemon, & Zeithaml, 2004), customer loyalty (Lam, Shankar, Erramilli, & Murthy, 2004), and customer satisfaction (Luo & Homburg, 2007),

when measuring marketing capabilities. Ambler et al. (2004) propose a simple two-stage framework where marketing action and activities serve as initial inputs. At the intermediate stage, brand-linked characteristics – such as customer memories, attitudes, awareness, loyalty, and commitment – lead to outcome measures, such as financial outcomes and customer satisfaction.

2. Research hypotheses

In this study, we define marketing capabilities as those intangible marketing activities that enable firms to improve the productivity of other resources owned by firms. This is consistent with the RBT framework, which states that capabilities improve the productivity of other resources, and the market-based resources perspective, which states that intangible, complementary resources have greater impact on SCA. We propose a non-radial two-stage Data Envelopment Analysis (DEA) model that identifies and measures intangible marketing and operations efficiencies in an integrated fashion in the healthcare industry – specifically, in the hospital industry. This allows us to integrate multiple resources synergistically to explain their differential effects on firm performance. The biggest contribution of this study is the use of intangible marketing assets, such as brand familiarity, loyalty, reputation, and referrals, in measuring marketing capabilities (brand mind share or brand equity). A key construct in marketing, brand equity is one of the major intangible marketing assets (Ambler, 2003). Aaker (1996, pp. 7-8) defines brand equity as "a set of assets and liabilities linked to a brand, its name and symbol, which add to or subtract from the value provided by a product or service to a firm and/or that firm's customers." Brand equity has been shown to have a positive impact on "customer mindset outcomes" (Mirzaei, Gray, & Baumann, 2011) such as brand awareness, loyalty, reputation, and referrals. While the importance of operational efficiency in driving firm performance is well established (Hitt et al., 2016), researchers advocating for a marketing-operations interface found strong empirical evidence that firms can coordinate their marketing and operations to improve their competitiveness and profit (Hausman et al., 2002; Ho & Tang, 2009; Nath et al., 2010; Sawhney & Piper, 2002). The literature therefore suggests that:

> H1: A firm's intangible marketing efficiency has a positive impact on its performance.
> H2: A firm's operational efficiency has a positive impact on its performance.
> H3: The interface between a firm's intangible marketing and operational efficiency has a positive impact on its performance.

In the following sections, we will first present a literature review of DEA and its applications in benchmarking hospital performance. We then present the conceptual DEA model for our study and empirically test it. We also present the results of a path analysis to test the relationships of the intangible marketing variables. Last, we discuss the managerial and academic implications of our research.

3. Literature review: DEA models to evaluate the efficiency of hospitals

The DEA model has been extensively used in the analysis of hospital performance. Some studies have applied the basic DEA model to evaluate hospital efficiency. For instance, Linna, Häkkinen, and Magnussen (2006) used the DEA model to measure cost efficiency across countries. In a simulation that includes several scenarios for hospital emergency division, Al-Refaie, Fouad, Li, and Shurrab (2014) used the basic DEA model to measure efficiencies for those scenarios. Other studies have tried to modify the DEA model to obtain more precise efficiency measurement for hospitals. Butler and Li (2005) measured the efficiency and effectiveness of resource utilization in hospitals by using the return-to-scale analysis, which was developed based on the DEA model. Wei,

Chen, Li, and Tsai (2011) proposed the ratio-based DEA model, which is able to solve the problem of pseudo-inefficiency to measure hospital efficiency. Wei, Chen, Li, Tsai, and Huang (2012) further developed another ratio-based DEA model that reduces redundant restraints from previous work.

Because the input and output of hospital operations characterize multiple variables, an increasing number of researchers have focused on improving the use of variables. Kao, Lu, and Chiu (2011) extracted hospital inputs through the component analysis in efficiency measurement. Castelli, Street, Verzulli, and Ward (2015) applied aggregated variables that combine diverse inputs and outputs with intensity weights, such as cost, quality, and expenditure ratios, to reduce the numbers of inputs and outputs. Alonso, Clifton, and Díaz-Fuentes (2015) defined mortality and readmission rates to be undesirable outputs in the evaluation of hospitals. Mitropoulos, Talias, and Mitropoulos (2015) assumed hospital outputs as stochastic variables and established a modified DEA model to assess the efficiencies of various hospital types. Ouellette and Vierstraete (2004) proposed another modified DEA model in which part inputs are assumed to be quasi-fixed factors to measure hospital efficiency and technological change.

Another stream of research analyzes hospital performance from a dynamic viewpoint and time-cross changes on efficiency and technology. Kazley and Ozcan (2009) applied the inter-temporal DEA model to measure the change of efficiency and explored the influence of electronic medical records on the change. Ng (2011) assessed inter-temporal productive efficiency for hospitals and discussed the difference between regions. Chang, Hsiao, Huang, and Chang (2011) measured the inter-temporal changes of productivity, quality, efficiency, and technology in hospitals. Hsu (2013) used country-level data to analyze the inter-temporal efficiency of government spending on health. Chowdhury, Zelenyuk, Laporte, and Wodchis (2014) added the factor of case-mix adjustment into the inter-temporal DEA model to assess hospital efficiency and technological changes.

External influence on efficiency has also become an important issue in many hospital studies. Researchers apply the DEA model to assess efficiency and also use regression models to estimate the relationship between external factors and efficiency. For instance, Chang (1998) measured hospital efficiency with the DEA model and estimated the significance of occupancy rates and the proportion of elderly patients on efficiency. Puig-Junoy (2000) looked at external factors, such as nonprofit or for-profit types, market concentration, and number of competitors. Watcharasriroj and Tang (2004) analyzed the effects of hospital size and information technology (IT) investment on hospital efficiency. Chang, Chang, Das, and Li (2004) investigated the influence of the adoption of National Health Insurance on efficiency and found that the insurance program has a negative impact on hospitals. In addition to external influence on hospital efficiency, Chen, Hwang, and Shao (2005) also explored the sources of inefficiency caused by inputs. Leleu, Moises, and Valdmanis (2014) discussed the impact of factorial inefficiency of inputs on profits for hospitals. Investigating the relationship between IT and hospital efficiency, Gholami, Higón, and Emrouznejad (2015) found a U-shaped relationship.

Other researchers have looked at hybrid models. Some have considered the combination of the DEA and the analytical hierarchy process (AHP) in efficiency assessment (Kim, Jeon, Cho, & Kim, 2018; Rouyendegh, Oztekin, Ekong, & Dag, 2016; Yang, 2010). Yang (2010) designed the DEA-AHP hybrid model to evaluate efficiency of regional public hospitals in Korea. Rouyendegh et al. (2016) developed an approach that uses the fuzzy AHP to enhance the data and structure of the DEA model to evaluate efficiency in the health-care industry. Kim et al. (2018) also used the two models to analyze the eco-efficiencies of hospitals in South Korea.

In addition to quantitative indices, some qualitative indicators are gradually incorporated into hospital efficiency measurement. Defining quality indicators such as mortality rate and length of stay for hospitals,

Yang and Zeng (2014) applied the DEA model to show the trade-off between efficiency and quality. van Ineveld, van Oostrum, Vermeulen, Steenhoek, and van de Klundert (2016) added quality indicators – represented by the percentage of decubitus ulcers (bedsores) prevalent in patients – into the output set to assess efficiencies for hospitals. Gok and Sezen (2013) collected information about patient satisfaction through interviews and mail surveys, then used the DEA model to estimate the relationship between patient satisfaction and hospital efficiency.

In a cross-national comparison of 79 DEA-based hospital efficiency studies between 1984 and 2004, O'Neill, Rauner, Heidenberger, and Kraus (2008) did not find any study that has looked at intangible marketing assets. Industries offering services with high experience or credence, such as healthcare, benefit from having strong relational and brand resources (Palmatier, Dant, Grewal, & Evans, 2006). One of the critical conditions in VRIO, intangible resources (such as marketing assets) are often harder to imitate. In this study, our methodology enables hospitals to capture not only the individual effect of each capability but also their interdependencies. The DEA methodology also allows hospitals to benchmark their operations and marketing efficiencies not only within their firm but also with other competitors (between-group benchmarking). Our study also looks at how intangible marketing assets are related in a path analysis in order to examine their relationship with consumers' overall satisfaction and their likelihood of referring the hospital to their friends and family.

4. Methodology

4.1. Two-stage DEA model

Charnes, Cooper, and Rhodes (1978) and Banker, Charnes, and Cooper (1984) primarily proposed the basic DEA model, which uses multiple inputs and outputs to compute an efficiency index based on the mathematical planning approach. The conventional DEA model has been extended to become a multiple-stage framework, which assesses various performance indicators and uses the concept of intermediate linking efficiency indices. For example, Yu and Lee (2009), Chiu and Huang (2011), and Lin, Chiu, and Huang (2012) applied the two-stage DEA model to evaluate efficiency and effectiveness indicators. Chiu, Huang, and Ma (2011) incorporated intermediate inputs and outputs into the two-stage framework. Yu and Lin (2008), Yu (2010), Hsieh and Lin (2010), Wang, Lu, Huang, and Lee (2013), and Huang, Ho, and Chiu (2014) further assumed that there are different divisions in a single stage.

In the empirical model of this study, we develop a non-radial two-stage DEA model to analyze the performance of intangible marketing assets and operations of hospitals. Brand and its impact has been the most studied aspect of market-based resources (Kozlenkova et al., 2014). For example, research has shown a positive effect of brand management on performance (Morgan et al., 2009). In our model, we propose that advertising efficiency affects brand mind share (brand familiarity, image/reputation, and brand loyalty), which leads to customer satisfaction and referrals.

Advertising efficiency is measured in the first stage, and operational efficiency in the second. We use the advertisement image influence as the initial input. Advertising image influence is measured by the percentage of respondents who responded that the hospital's advertisement had a positive influence on the image of the hospital (measured as 1 = positive, 2 = negative, 3 = no influence).[2] The concept of brand mind share is assumed as the intermediate output linking the stages of marketing and operations. Brand familiarity is measured as the mean of respondents who are very familiar with the hospital (measured from

---

[2] All ratio calculations for marketing variables are based on the percentage of respondents who selected a category divided by the total number of respondents.

0 = not at all familiar to 100 = very familiar). Brand image/reputation is measured as the mean of respondents who believe the hospital is the best in the market (measured from 0 = worst in the market to 100 = best in the market). Brand loyalty is measured as the mean of respondents who only choose the hospital they use (measured from 1 = "It's the only hospital I would use" to 5 = "I would not use it").

Intermediate inputs, or inputs for the second stage that are not generated from the first stage (Chiu, Huang, & Ting, 2011), include total assets, total operating expenses, and number of hospital beds. Total assets refer to the sum of all current, fixed, and other assets (measured in million US$). Total operating expenses refer to the sum of all expenses incurred during the ordinary course of operating the hospital (measured in million US$). Beds in service refer to the sum of beds available for adults, pediatrics, intensive care, sub-providers, skilled nursing facilities, and distinct hospice. Final output is presented with two different indicators, financial output and patients' satisfaction. Net patient revenues refers to the total patient revenue less allowances and discounts on patient accounts (measured in million US$). Satisfaction is measured with two indicators – satisfaction with overall care, and service and referral. Satisfaction with overall care and service denote the mean of respondents who consider the overall quality of care and services to be excellent (measured from 0 = poor to 100 = excellent). Referral is measured as the mean of respondents who would definitely recommend the hospital to friends and family (measured from 0 = definitely not to 100 = definitely yes). The graphical representation for the DEA framework of hospital performance measurement is shown in Fig. 1.

The two-stage model, which is assumed as a non-oriented and non-radial measurement, is designed as follows. We suppose that observations are a J dimension decision-making unit (DMU) set, and the individual unit is represented as $DMU_j (j = 1, \cdots, J)$. The DMU under evaluation is represented as DMU_O, which is subject to $DMU_O \in J$. Factors of initial input and intermediate input, which are used to measure advertising efficiency in the first stage, are defined as $x_m \in R_+^M$ and $z_n \in R_+^N$, respectively. An intensity variable, λ_j, which is assumed unknown before solving and represents the weights of benchmarking units, is defined in order to solve the mathematical planning. The technology set of the first stage can be formulated as:

$$Tech^{1st}\{(x, z): \sum_{j=1}^{J} \lambda_j x_{mj} \leqslant x_m (\forall\, m), \sum_{j=1}^{J} \lambda_j z_{nj} \geqslant z_n (\forall\, N), \sum_{j=1}^{J} \lambda_j = 1, \lambda_j \geqslant 0, \forall\, j\}$$

(1)

We define the intermediate input, which characterizes an input used in the second stage that is not generated from the first stage, as

$w_k \in R_+^K$. Therefore, there are two input types, including intermediate output (z_n) generated from the first stage and intermediate input (w_k) not generated from the first stage, for the second-stage efficiency. The final output produced from the second stage is labeled as $y_l \in R_+^L$. We also define the intensity variable, μ_j, for the mathematical planning of the second stage. The technology set of the second stage can be formulated as:

$$Tech^{2nd}\{(z, w, y): \sum_{j=1}^{J} \mu_j z_{nj} \leqslant z_n (\forall\, n), \sum_{j=1}^{J} \mu_j w_{kj} \leqslant w_k (\forall\, k), \sum_{j=1}^{J} \mu_j y_{lj} \geqslant y_l, (\forall\, l), \sum_{j=1}^{J} \mu_j = 1, \mu_j \geqslant 0, \forall\, j\}$$

(2)

Then, the overall technology set can be defined in accordance with the assumptions of the first and second stages as:

$$Tech^{overall}\{(x, z, w, y): \sum_{j=1}^{J} \lambda_j x_{mj} \leqslant x_m (\forall\, m), \sum_{j=1}^{J} \lambda_j z_{nj} \geqslant z_n (\forall\, n), \sum_{j=1}^{J} \mu_j z_{nj} \leqslant z_n (\forall\, n), \sum_{j=1}^{J} \mu_j w_{kj} \leqslant w_k (\forall\, k), \sum_{j=1}^{J} \lambda_j y_{lj} \geqslant y_l (\forall\, l), \sum_{j=1}^{J} \lambda_j = 1, \sum_{j=1}^{J} \mu_j = 1, \lambda_j \geqslant 0, \mu_j \geqslant 0, \forall\, j\}$$

(3)

To evaluate efficiencies in a non-radial measure, we transfer the overall technology set to be the following:

$$Tech^{overall}\{(x, z, w, y): \sum_{j=1}^{J} \lambda_j x_{mj} = x_m - s_m^- (\forall\, m),$$

$$\sum_{j=1}^{J} \lambda_j z_{nj} = z_n + s_n^+ (\forall\, n)$$

$$\sum_{j=1}^{J} \mu_j z_{nj} = z_n - s_n^- (\forall\, n), \sum_{j=1}^{J} \mu_j w_{kj} = w_k - s_k^- (\forall\, k),$$

$$\sum_{j=1}^{J} \mu_j y_{lj} = y_l + s_l^+ (\forall\, l)$$

$$\sum_{j=1}^{J} \lambda_j = 1, \sum_{j=1}^{J} \mu_j = 1, \lambda_j, \mu_j, s_m^-, s_k^-, s_n^+, s_n^-, s_l^+ \geqslant 0, \forall\, j\}.$$

(4)

In formula (4), the variables $s_m^- (\forall\, m)$ and $s_k^- (\forall\, k)$ represent the slacks of initial and intermediate inputs, respectively. Input slack means the excessive input utilizations in the operation of the DMU_O. The

Initial input:
Advertisement image influence

Advertising Efficiency

Intermediate outputs:
1. Brand familiarity
2. Brand image/reputation
3. Brand loyalty

Intermediate inputs:
1. Total assets
2. Total Operating Expenses
3. Beds in service

Hospital Efficiency

Final outputs:
1. Net Patient Revenue
2. Satisfaction
   a. Overall satisfaction
   b. Referral
      (Friends/Family)
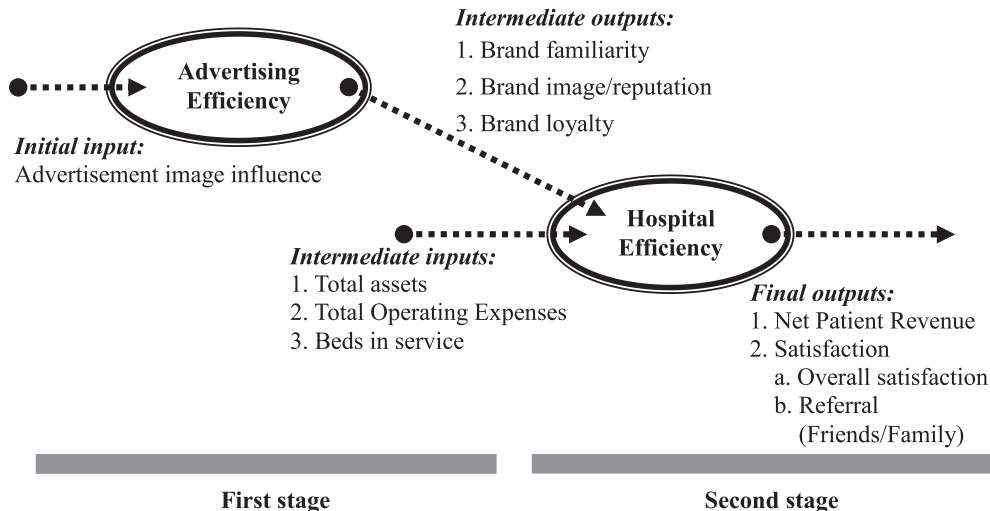
First stage   **Second stage**

Fig. 1. Two-stage analysis of marketing efficiency and hospital operations efficiency.

variable $s_l^+ (\forall\ l)$ represents the slack of the final input, i.e., the shortfall of output. The slack of intermediate output is defined as $s_n^+ (\forall\ n)$ in the first stage; and the same item, which represents excess of intermediate output for the second stage, is defined as $s_n^- (\forall\ n)$. Entire slack variables are fully set as unknown in the model. According to the definition of the overall technology set, the two-stage DEA model is described as:

$$\begin{aligned} \underset{\lambda,\mu,s_m^+,s_k^-,s_n^-,s_n^+s_l^+}{\rho^*} &= Min \quad \rho \\ \text{s. t.} \sum_{j=1}^{J} \lambda_j x_{mj} &= x_{mo} - s_m^- (\forall\ m), \\ \sum_{j=1}^{J} \lambda_j z_{nj} &= z_{no} + s_n^+ (\forall\ n), \\ \sum_{j=1}^{J} \mu_j z_{nj} &= z_{no} + s_n^- (\forall\ n), \\ \sum_{j=1}^{J} \mu_j w_{kj} &= w_{ko} - s_k^- (\forall\ k), \\ \sum_{j=1}^{J} \mu_j y_{lj} &= y_{lo} + s_l^+ (\forall\ l), \\ \sum_{j=1}^{J} \lambda_j &= 1, \ \sum_{j=1}^{J} \mu_j = 1, \\ \lambda_j, \mu_j, s_m^-, s_k^-, s_n^+, s_n^-, s_l^+ &\geqslant 0, \ \forall\ j. \end{aligned} \tag{5}$$

In formula (5), the objective value of the mathematical planning program is defined as ρ, which is formed as:

$$\rho = \sum_{m=1}^{M} s_m^- + \sum_{k=1}^{K} s_k^- + \sum_{n=1}^{N} s_n^+ + \sum_{n=1}^{N} s_n^- \sum_{n=1}^{N} s_l^+ \tag{6}$$

The optimal solutions on slack variables (shown as s_m^{-*}, s_l^{+*}, s_n^{-*}, s_n^{+*} and s_k^{-*}) and objective value (shown as ρ^*) can be solved through an optimization procedure of the mathematical planning program. The overall efficiency index can be formulated based on the optimal slack values as:

$$\begin{aligned} Eff^{overall} &= \left[1 - \frac{1}{M + K + N} \cdot \left(\sum_{m=1}^{M} \frac{s_m^{-*}}{x_{mo}} + \sum_{k=1}^{K} \frac{s_k^{-*}}{w_{ko}} + \sum_{n=1}^{N} \frac{s_n^{-*}}{z_{no}} \right) \right] \\ &\cdot \left[1 + \frac{1}{L + N} \cdot \left(\sum_{l=1}^{L} \frac{s_l^{+*}}{y_{lo}} + \sum_{n=1}^{N} \frac{s_n^{+*}}{z_{no}} \right) \right]^{-1} \end{aligned} \tag{7}$$

According to the optimal slack values, the first- and second-stage efficiency indices can be defined as follows:

$$\text{First} - \text{stage efficiency: } Eff^{1st} = \left(1 - \frac{1}{M} \cdot \sum_{m=1}^{M} \frac{s_m^{-*}}{x_{mo}} \right) \left(1 + \frac{1}{N} \cdot \sum_{n=1}^{N} \frac{s_n^{+*}}{z_{no}} \right)^{-1} \tag{8}$$

$$\begin{aligned} \text{Second} &- \text{stage efficiency: } Eff^{2nd} \\ &= \left[1 - \frac{1}{K + N} \cdot \left(\sum_{k=1}^{K} \frac{s_k^{-*}}{w_{ko}} + \sum_{n=1}^{N} \frac{s_n^{-*}}{z_{no}} \right) \right] \cdot \left(1 + \frac{1}{L} \cdot \sum_{l=1}^{L} \frac{s_l^{+*}}{y_{lo}} \right)^{-1} \end{aligned} \tag{9}$$

We further use the optimal values of slacks to define the factorial efficiency indices, which can reveal the sources of inefficiency from excessive input use and deficit of output, as follows:

$$\text{Factorial efficiency of the } m\text{th initial input: } Eff^{in} = \frac{x_{mo} - s_m^{-*}}{x_{mo}} (\forall\ m) \tag{10}$$

$$\text{Factorial efficiency of the } l \text{ th final output: } Eff^{out} = \frac{y_{lo}}{y_{lo} + s_l^{+*}} (\forall\ l) \tag{11}$$

Factorial efficiency of the k th intermediate input: Eff^{iin}

$$= \frac{w_{ko} - s_k^{-*}}{w_{ko}} (\forall\ k) \tag{12}$$

Factorial efficiency of the n th intermediate output: Eff^{iout}

$$= \frac{z_{no} - s_n^{-*}}{z_{no} + s_n^{+*}} (\forall\ n) \tag{13}$$

4.2. Empirical data

The data used to test our model comes from the National Research Corporation's (NRC) Market Insights Core Survey,[3] the largest online U.S. health care survey. It measures the opinions and perceptions of about 300,000 health-care customers annually in many areas, including their hospital preferences and perceptions. NRC fields the data in nearly 300 markets across the country, and the data is weighted to represent the overall U.S. population.

Given the exploratory and expository nature of our study (and license restriction), we employ a multistage sampling approach in selecting our restricted sample data. We initially selected respondents in two of the largest states in the western United States – California and Washington – to maximize our sample size for the year 2013 (the latest year available at the time of this study). There are 430 hospitals in California and 108 hospitals in Washington. Since we are testing hospital performance, all consumer data is rolled up to the hospital level; that is, all hospital data is aggregated from consumers according to their respective individual hospital. The next stage is to merge this marketing data with hospital operational and financial data, which is obtained from the American Hospital Association (https://www.ahadataviewer.com/). The AHA database includes over 1000 data fields, including firmographics, operational data (such as number of beds, number of specialties, etc.), and financial data (such as revenue, expenses, etc.). To test our DEA model, we chose only hospitals that have complete financial and operational data. This results in a total of 47 hospitals from both states (24 from Washington and 23 from California). Using two states allows us to show any regional differences in hospital efficiencies (Ng, 2011). The total number of consumers associated with the hospitals in Washington is 3112; the number in California is 5407. Due to a potential sample selection bias, our multistage approach in selecting a restricted sample may not be representative of the population and may bias the results of the study.

The initial input used to measure advertising efficiency is advertisement image influence. Brand mind share - which includes brand familiarity, brand image/reputation, and brand loyalty - is assumed as the intermediate output. Total assets, total operating expenses, and total number of beds in service are used as intermediate inputs to evaluate operational efficiency. The final output set consists of net patient revenues, the degree of satisfaction on overall service, and referral (friends/family). The specific description for all factors is shown below, and the descriptive statistics are reported in Table 1.

Initial input:

- Advertisement image influence refers to the ratio of respondents for whom a hospital's advertisement has had a positive influence on their image of the hospital (scale: 1 = positive, 2 = negative, 3 = no influence).
- Intermediate output:
- Brand familiarity refers to the mean of respondents who are very familiar with the hospital (measured from 0 = not at all familiar to 100 = very familiar).
- Brand image/reputation refers to the mean of respondents who consider the hospital to be the best in the market (measured from 0 = worst in the market to 100 = best in the market).
- Brand loyalty refers to the mean of respondents who only choose the hospital they use (measured from 1 = "It is the only hospital I would use" to 5 = "I would not use it").

Table 1
Descriptive statistics.

	Mean	Std. Dev.	Max.	Min.
Advertisement image influence (%)	67.4	8.6	85.7	49.5
Brand loyalty (%)	20.2	6.8	36.3	8.5
Brand image/reputation (%)	75.7	8.0	90.4	56.9
Brand familiarity (%)	70.2	5.4	81.1	52.7
Total assets (million US$)	951.1	1005.2	4282.4	22.6
Total operating expenses (million US$)	604.2	548.2	2334.5	72.2
Total beds in service for facility (%)	344.9	203.2	896.0	41.0
Net patient revenue (million US$)	631.5	587.8	2479.6	91.3
Satisfaction of overall care and service (%)	84.3	4.7	91.6	73.9
Referral (Friends/Family) (%)	86.3	5.5	94.8	74.4

Intermediate input:

- Total assets refers to the sum of current, fixed, and other assets (measured in million US$).
- Total operating expenses refers to the sum of the expenses incurred during the ordinary course of operating the hospital (measured in million US$).
- Beds in service refers to the sum of beds in service for adults, pediatrics, intensive care, sub-providers, skilled nursing facilities, and distinct hospice.

Final output:

- Net patient revenue refers to total patient revenue less allowances and discounts on patient accounts (measured in million US$).
- Satisfaction with overall care and service refers to the mean of respondents who consider the overall quality of care and services (average total utilization based on hospital inpatient stay, hospital emergency room, outpatient/same-day surgery, and outpatient testing/x-rays) of the hospital to be excellent (measured from 0 = poor to 100 = excellent).
- Referral (Friends/Family) refers to the mean of respondents who would definitely recommend the hospital to family and friends (average total utilization based on hospital inpatient stay, hospital emergency room, outpatient/same-day surgery, and outpatient testing/x-rays) of the hospital (measured from 0 = definitely not to 100 = definitely yes).

5. Empirical results

This study uses the MS Excel solver add-in to program the empirical model and compute efficiency scores. The results of performance indicators evaluated by using the two-stage DEA model are shown in Table 2. The first column shows the number code for hospitals.[4] The location of hospitals is shown in the second column ("WA" represents Washington State and "CA" represents California). Advertising efficiency (i.e.,) is reported in the third column. There are 13 hospitals that achieve best practice in their advertising activities and have a score equal to one. The fourth column shows the result of operational efficiency (i.e., Eff^{2nd}), in which 22 hospitals are evaluated as efficient, with an efficiency score equal to one. The fifth column shows the results of overall performance (i.e., $Eff^{overall}$). Six hospitals (13, 16, 20, 25, 27, and 45) are assessed as performing efficiently in both their advertising and operation processes.

Comparing advertising and operational performance in hospitals, there are 23 hospitals that have a higher score for advertising efficiency, and there are 18 hospitals that have a higher score for operational efficiency. The average difference between the two indices is

_____

[4] Due to non-disclosure agreement with data providers, hospital names have been withheld.

Table 2
Results of performance indicators.

No.	Region	Advertising efficiency	Operational efficiency	Overall performance
01	WA	0.923	0.468	0.593
02	WA	0.872	1	0.932
03	WA	0.727	0.713	0.675
04	WA	1	0.556	0.661
05	WA	0.790	1	0.883
06	WA	0.487	1	0.659
07	WA	0.649	1	0.787
08	WA	1	0.537	0.627
09	WA	0.810	0.546	0.598
10	WA	0.643	0.745	0.676
11	WA	0.812	0.472	0.533
12	WA	0.802	0.610	0.646
13	WA	1	1	1
14	WA	0.718	1	0.836
15	WA	0.843	1	0.915
16	WA	1	1	1
17	WA	1	0.863	0.882
18	WA	0.748	1	0.856
19	WA	0.494	1	0.661
20	WA	1	1	1
21	WA	0.578	1	0.733
22	WA	0.741	0.798	0.705
23	WA	0.717	1	0.835
24	WA	0.900	0.647	0.710
25	CA	1	1	1
26	CA	0.826	0.626	0.631
27	CA	1	1	1
28	CA	1	0.537	0.620
29	CA	1	0.629	0.683
30	CA	0.970	1	0.985
31	CA	0.700	1	0.823
32	CA	0.939	0.536	0.599
33	CA	0.877	0.548	0.579
34	CA	0.758	1	0.862
35	CA	1	0.629	0.683
36	CA	0.703	0.545	0.550
37	CA	0.767	0.490	0.552
38	CA	0.934	0.425	0.553
39	CA	0.792	1	0.884
40	CA	0.938	0.421	0.543
41	CA	1	0.512	0.641
42	CA	0.810	0.590	0.589
43	CA	0.773	1	0.872
44	CA	0.779	0.613	0.604
45	CA	1	1	1
46	CA	0.726	1	0.841
47	CA	0.951	0.719	0.741
Mean		0.840	0.782	0.750

0.251, and only four hospitals (06, 19, 38, and 40) have a significant difference higher than 0.500. To test our hypotheses, we ran an independent samples *t*-test comparing the overall performance between hospitals that are considered efficient (scores equal to 1) and those that are not (score less than 1). For advertising efficiency, there is a significant difference (p = .024) between efficient (μ = 0.83) and inefficient (μ = 0.72) hospitals; thus, there is support for H1. For operational efficiency, there is a significant difference (p = .000) between efficient (μ = 0.88) and inefficient (μ = 0.63) hospitals; thus, there is support for H2. For hospitals that are efficient in both advertising and operational efficiency, there is a significant difference (p = .000) between efficient (μ = 1) and inefficient (μ = 0.71) hospitals; thus, there is support for H3. The results show both the main and interaction effects of advertising and operational efficiency in the overall performance of hospitals.

The results of factorial efficiencies for initial input (i.e., Eff^{in}) and final output (i.e., Eff^{out}) are reported in Table 3. For initial input (advertisement image influence), it shows that hospitals are mostly efficient. Only three hospitals (06, 26, and 44) have a score less than one. A potential explanation and bias for this advertising image influence

Table 3
Results of factorial efficiencies of initial input and final output.

No.	Initial input	Final output		
	Advertisement image influence	Net patient revenue	Satisfaction of overall care and service	Referral (Friends/ Family)
01	1	0.323	0.976	1
02	1	1	1	1
03	1	0.683	1	0.947
04	1	0.543	0.990	1
05	1	1	1	1
06	0.988	1	1	1
07	1	1	1	1
08	1	0.697	0.987	0.967
09	1	0.507	0.972	0.981
10	1	0.555	0.989	1
11	1	0.501	0.962	1
12	1	0.531	0.980	1
13	1	1	1	1
14	1	1	1	1
15	1	1	1	1
16	1	1	1	1
17	1	1	1	1
18	1	1	1	1
19	1	1	1	1
20	1	1	1	1
21	1	1	1	1
22	1	1	0.994	1
23	1	1	1	1
24	1	0.565	0.993	1
25	1	1	1	1
26	0.924	1	0.994	1
27	1	1	1	1
28	1	0.756	0.994	1
29	1	1	0.980	1
30	1	1	1	1
31	1	1	1	1
32	1	0.779	1	0.976
33	1	0.950	0.942	1
34	1	1	1	1
35	1	1	0.987	1
36	1	0.534	0.992	1
37	1	0.406	0.971	0.963
38	1	0.312	0.974	1
39	1	1	1	1
40	1	0.345	0.974	1
41	1	0.401	0.993	1
42	1	0.896	0.968	1
43	1	1	1	1
44	0.994	0.787	0.998	1
45	1	1	1	1
46	1	1	1	1
47	1	1	0.994	1
Mean	0.998	0.831	0.992	0.996

Table 4
Results of intermediate factors.

No.	Intermediate output			Intermediate input		
	Brand loyalty	Brand image/ reputation	Brand familiarity	Total assets	Total operating expenses	Total beds in service
01	0.517	0.992	0.901	1	0.796	0.455
02	0.824	0.933	0.865	1	1	1
03	0.517	0.839	0.837	0.470	0.941	0.773
04	0.491	0.890	0.791	0.641	0.704	0.762
05	0.613	1	0.858	1	1	1
06	0.300	0.672	0.789	1	1	1
07	0.388	1	0.961	1	1	1
08	0.747	1	0.915	0.164	0.454	0.463
09	0.446	0.901	0.911	0.353	0.632	0.734
10	0.408	0.872	0.631	0.967	1	0.725
11	0.504	0.964	0.892	0.307	0.471	0.306
12	0.471	0.892	0.846	0.863	0.703	0.540
13	1	1	1	1	1	1
14	0.481	0.936	0.97	1	1	1
15	0.641	1	1	1	1	1
16	1	1	1	1	1	1
17	1	0.966	0.951	1	0.659	0.601
18	0.517	1	0.929	1	1	1
19	0.269	0.817	0.890	1	1	1
20	1	1	1	1	1	1
21	0.319	1	0.953	1	1	1
22	0.505	0.997	0.898	0.472	0.520	0.854
23	0.598	0.758	0.837	1	1	1
24	0.477	0.890	0.841	0.848	0.816	0.787
25	1	1	1	1	1	1
26	0.496	0.881	0.793	0.259	0.464	0.629
27	1	1	1	1	1	1
28	0.567	0.893	0.870	0.282	0.461	0.503
29	0.439	1	0.906	0.323	0.514	0.617
30	0.915	1	0.999	1	1	1
31	0.545	0.973	0.701	1	1	1
32	0.583	0.936	0.906	0.130	0.417	0.461
33	0.558	0.806	0.844	0.158	0.449	0.307
34	0.620	0.931	0.786	1	1	1
35	0.953	0.870	0.856	0.408	0.419	0.285
36	0.474	0.948	0.891	0.298	0.542	0.404
37	0.409	0.846	0.893	0.316	0.856	0.636
38	0.497	0.952	0.883	0.406	0.842	0.728
39	0.597	0.944	0.949	1	1	1
40	0.565	1	0.899	0.364	0.762	0.443
41	0.540	1	0.933	0.526	0.846	0.760
42	0.463	0.876	0.826	0.349	0.435	0.342
43	0.579	0.985	0.880	1	1	1
44	0.493	0.884	0.781	0.268	0.563	0.578
45	1	1	1	1	1	1
46	0.509	1	0.857	1	1	1
47	0.509	0.969	0.864	0.642	0.639	0.583
Mean	0.603	0.936	0.895	0.719	0.806	0.772

efficiency could be that 67% of respondents indicated that hospitals' advertisements had a positive influence on their perceptions/image of the hospital. One might assume, ceteris paribus, that respondents would tend to go to the hospital for which they have a positive image. The factorial efficiencies of net patient revenues, satisfaction with overall care and service, and referral are shown under the heading "Final input." For net patient revenues, there are 28 hospitals that are assessed as efficient. For satisfaction with overall care and service, there are 25 hospitals that are assessed as efficient. For referral likelihood, there are 42 hospitals that are assessed as efficient. For hospitals whose factorial efficiency scores for both satisfaction and referral are evaluated as less than one, all are higher than 0.900. However, for net patient revenue efficiency, the scores for inefficient hospitals are evaluated under 0.900 (mean = 0.831). We find that the shortfall of net patient revenues is the principal factor behind hospitals' inefficiency, not the impact of lower satisfaction of overall care and service and referral (friends/family).

The results of factorial efficiency of intermediate outputs (i.e.,

Eff^{iout}) are reported in Table 4. The scores for brand loyalty, reputation, and familiarity are shown under the heading of "Intermediate output." The number of hospitals that are assessed as efficient for brand loyalty and brand familiarity are both 7, and the number of hospitals that are efficient for brand reputation is 17. The results indicate that lower brand loyalty (mean efficiency = 0.603) is causing lower performance in hospitals' advertising activities and operations. Relatively, most hospitals obtain better brand image/reputation and brand familiarity through their advertisements.

The results of factorial efficiency of intermediate inputs (i.e., Eff^{iin}) are shown under the heading "Intermediate input" in Table 4. Twenty-four hospitals are efficient in total asset utilization; 23 are efficient in operating expenses utilization; and 22 are efficient in beds-in-service utilization. The average total operating expenses efficiency is highest at 0.806, and efficiencies for total assets and beds in service are 0.719 and 0.772, respectively. The results show the under-utilization of total assets and total beds in service as compared to total operating expenses

Table 5
Average performance indicators.

Performance indicator	Overall average	Regional average	
		Washington	California
Overall performance	0.750	0.767	0.732
Advertisement efficiency	0.840	0.802	0.880
Operational efficiency	0.782	0.831	0.731
Factorial efficiency			
Initial input:			
Advertisement image influence	0.998	1.000	0.996
Intermediate output:			
Brand loyalty	0.603	0.585	0.622
Brand image/reputation	0.936	0.930	0.943
Brand familiarity	0.889	0.890	0.883
Intermediate input:			
Total assets	0.719	0.837	0.597
Total operating expenses	0.806	0.862	0.748
Total beds in service	0.772	0.833	0.708
Final output:			
Net patient revenue	0.831	0.829	0.833
Satisfaction of overall care and service	0.992	0.993	0.990
Referral (Friends/Family)	0.996	0.996	0.997

control.

Table 5 reports the average performance indicators for hospitals. In addition to the average for all hospitals, we also classify hospitals into two groups according to their state of domicile. One of the advantages of DEA is that it allows us to compare benchmark scores across different groups, such as between the two states. The average for all hospitals is listed in the second column under the heading of "Overall average." The average for overall performance is 0.750. The average for advertisement efficiency is 0.840, which is higher than the operational efficiency of 0.782. The efficiency for advertisement image influence is 0.998. For intermediate outputs, the average for brand image/reputation and familiarity is 0.936 and 0.889, respectively. Both are much higher than the average for brand loyalty, 0.603. For intermediate inputs, the average for operating expenses is 0.806, while the average for total assets is 0.719. For final output, satisfaction and referral indices are almost efficient at 0.992 and 0.996, respectively. The average efficiency for net patient revenues is 0.831. From the results above, we conclude that advertisement image influence, overall satisfaction, and referral have higher performance. However, for intermediate outputs, brand loyalty can be identified as the main source of inefficiency for hospitals. The average for intermediate inputs shows that under-utilization of total assets is the principal negative influence on hospitals' operational efficiency.

The average performance for Washington and California is reported under the heading of "Regional average" in Table 5. Comparing the two states, the results show that hospitals in Washington have a higher average for operational efficiency (0.831), but hospitals in California have a higher average for advertisement efficiency (0.880). For the average performance for both initial input and final outputs, there is not a significant difference between the two states. The average for brand loyalty and image/reputation in California is higher than in Washington. The average for intermediate inputs in Washington is higher than in California.

From the results, we find that hospitals in California have better performance for advertisement efficiency, and hospitals in Washington perform better for their operations. The lower performance for both brand loyalty and reputation has a negative influence on advertisement efficiency in Washington. In California, lower efficiency of total assets, operating expenses, and total number of beds in service results in lower operational efficiency.

5.1. Test for model specification

As our original DEA model includes only hospitals with complete data for all the tested variables, there may be potential omitted variable bias or missing data effects in our results. To test for these potential biases, we ran the same analysis by adding a new variable, "total facility personnel," which was initially excluded because it had 13 hospitals (28%) with missing information. In the revised model, total facility personnel is included as an intermediate input in the second stage. The two models were compared for performance indicators, and the Mann-Whitney tests were insignificant for both second-stage efficiency ($p = .86$) and overall efficiency ($p = .85$). These results provide more confidence in the results of our DEA model.

To test for the representativeness of our subset of hospitals from the other unselected hospitals in both states, we ran a series of independent-samples t-tests to compare them on the six marketing variables in the model. Of the six variables, three are significant (brand image/reputation, referrals, and overall satisfaction). This may indicate that there may be selection bias in our sample.

5.2. Intangible marketing assets path analysis

The outcome of our DEA analysis shows that advertisement efficiency is higher than operational efficiency in determining overall hospital efficiency. To determine how the intangible marketing variables are related, a path model based on the framework in Fig. 1 is tested using AMOS 24, based on the 47 hospital-level data. Fig. 2 shows the model that is estimated by path analysis.

Since our data came from a single online survey, it may introduce common method bias. If a single factor can explain the variance, it has significant common method bias. We tested for potential common method bias using the "Harman's single-factor test" to extract the
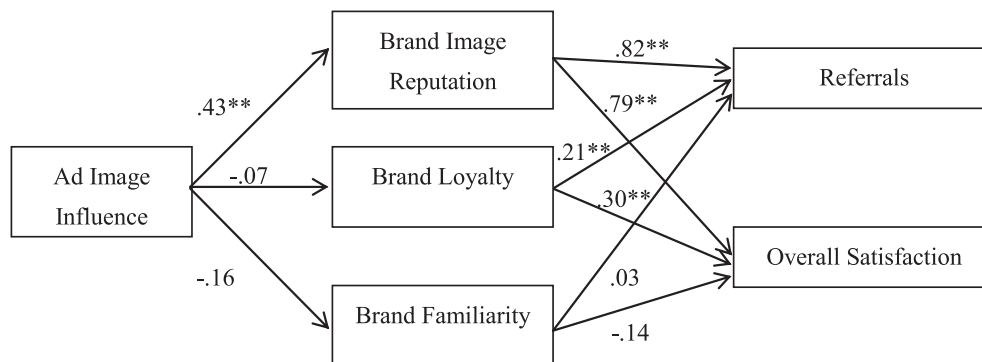
Fig. 2. Results of Path Analysis.

common variance (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003, p. 889). This diagnostic approach tests if (a) a single factor will emerge from the factor analysis or (b) one general factor will account for the majority of the covariance among the measures. We ran an exploratory factor analysis that includes all variables in the model. The results show a two-factor solution with the first factor accounting for 50.05% of the variance and 23.23% for the second factor. Despite its simplicity of use, however, the Harman's approach has its limitations. While the single-factor test may provide an indication of a single factor accounting for all of the covariances among the items, it does not statistically control for method effects (Podsakoff et al., 2003). In addition, there are no specific guidelines on how much variance the first factor should extract before it is considered a general factor. Another limitation is that the likelihood of obtaining more than one factor increases with the increase in the variables examined.

As the Harman's approach may not be a useful remedy to deal with common method bias, other researchers have suggested running a confirmatory factor analysis using a single unmeasured latent method factor method to test whether a single factor can account for all the variance. We included an unmeasured latent factor during the CFA that includes all measurement items. We then did a common method bias test by comparing the unconstrained common factor model to the zero-constrained model. The χ^2 difference between the two models is 126.3 (df = 6, p < .01). Even though the Harman's single-factor test shows potential method bias with a higher than recommended variance extraction; however, the more robust confirmatory factor analysis suggests we do not have a common method bias issue with our study. Regardless, it should be acknowledged that there might be potential method bias in our study.

The standardized path coefficients show that both brand image/reputation and brand loyalty positively influence consumers' overall satisfaction and referral likelihood. Brand familiarity does not affect hospitals' outcomes (referrals and overall satisfaction). Among the three mediator variables, only brand image/reputation is influenced by advertisement image influence. In other words, brand image positively mediates the relationship from advertisement image influence to hospitals' outcomes (referrals and satisfaction).

6. Conclusions

In this study, we establish a two-stage DEA model, based on the RBT framework, that evaluates the efficiencies of intangible marketing capabilities and operations for 47 hospitals in Washington and California. We use the concept of brand mind share - which includes brand loyalty, familiarity, and reputation - as the link between the two processes. In addition, our study looks at how the intangible marketing variables are related in a path model. The empirical results reveal several insights. On average, advertisement efficiency is higher than operational efficiency - which implies that hospitals' marketing activities, such as advertisements, are able to successfully raise consumers' awareness and increase hospitals' reputation and familiarity. However, increasing advertisement efficiency may not bring higher operational efficiency. This is likely due to the direct cost relationship between advertising activities and operational expenses. In addition, a hospital's reputation is built not only on advertising but also on adequate medical equipment and manpower. If not managed effectively, all of these investments would directly increase operating costs, which may lead to operational inefficiency. The overall results of the path analysis indicate that both image/reputation and loyalty are important factors in determining satisfaction and referrals. A hospital's advertising effort is more likely than loyalty to influence its brand image/reputation.

Another reason why marketing efficiency is higher than operational efficiency might be partially explained by the characteristics of the modeled technologies. In our DEA model, the technology modeling the marketing function includes an input-output set closely related to advertising efficiency (which may accurately capture the marketing

function), while the technology modeling operations efficiency may only partially capture total operations. The latter technology may suffer from specification bias, which may help to explain efficiency differences between the two functions (advertising efficiency and hospital efficiency). Although we tested for this specification bias in Section 4.1, there may be other variables that were not captured in the technology modeling operational efficiency.

Our study finds that the distribution of operational efficiencies is more dispersed than advertisement efficiency. Although fewer hospitals are evaluated as best practice for advertisement than operational efficiency, on average, the advertisement efficiency index is higher than operational efficiency. Most hospitals range between 0.700 and 0.900 for the advertisement efficiency index; on the other hand, inefficient hospitals have a score lower than 0.600 for operational efficiency. The finding implies that, with respect to advertising, the performance gap within hospitals is smaller than operational efficiency.

In addition, the results of factorial efficiencies indicate the under-utilization of total assets as the source of inefficiency for most hospitals. For brand mind share, brand loyalty has a lower factorial efficiency – that is, the lack of brand loyalty is the main factor resulting in inefficiency. Relatedly, most hospitals have higher efficiency for their brand image/reputation and brand familiarity.

From the factorial efficiency analysis (Table 3) for the final output, we find that the average efficiency scores for satisfaction with overall care and service and referral (friends/family) are higher than the average efficiency scores for net patient revenue. This suggests that satisfaction with overall care and service and referral (friends/family) does not necessarily translate to higher net patient revenue. This may be true if non-profit hospitals regard providing high-quality medical treatment and care to be a more important goal than achieving high profit margins.

Last, we find that hospitals in California perform better at advertisement efficiency, while hospitals in Washington have higher operational efficiency. Insufficient brand loyalty and reputation help to explain lower advertising efficiency for Washington hospitals, while inefficient use of assets, expenses, and total number of beds lowers operational efficiency for hospitals in California.

7. Implications

This paper addresses a methodological gap in incorporating the interdependencies of marketing capabilities with operation efficiencies in the healthcare industry at not only the individual hospital level, but also across hospitals. More importantly, by measuring the efficiency of marketing capabilities using intangible marketing assets, such as brand mind share, we provide important information regarding the contribution of intangible marketing capabilities to the overall operation of hospitals. In addition, our results give hospitals information about where their deficiencies may lie and how they can improve.

This paper holds important implications for both academic and managerial audiences. First, it proposes a more straightforward yet comprehensive tool than existing single-index financial performance tools. Second, it provides a methodological tool for the identification and measurement of marketing capabilities and operational efficiencies that accounts for their interdependencies. We identify the importance of marketing in the value-creation process, as well as which existing or new capabilities should be built for hospitals. Through path analysis, we are also able to look at the relationships among the intangible marketing variables to identify key success factors related to both consumer satisfaction and referrals. Third, our model allows for inter-hospital comparison, such that hospitals can benchmark against competitors, in terms of how efficient they are at deploying their marketing resources. Finally, it allows managers to identify their hospital's capabilities systematically and pinpoint critical areas that deserve immediate action. It can also be used on an ongoing basis to allow hospitals to track longitudinal performance trends. The proposed method

requires the active participation of all important stakeholders in a firm. The involvement, in turn, substantially facilitates strategy implementation by increasing the level of understanding and acceptance of the developed strategy.

8. Limitations and future research

Although our exploratory research offers valuable managerial insights for researchers and practitioners, it has limitations that may offer opportunities for future research. Our DEA approach of modeling hospitals' technology as a function where assets (number of beds and total assets) and operating expenses generate patient revenues, and customer satisfaction may potentially be exposed to bias resulting from misspecification issues. Future research may incorporate other factors in the technology function, such as the optimization of their labor pool (number of doctors, nurses, and other facility personnel) and medical objectives, such as average hospitalization days. Other marketing capabilities, such as the costs and benefits of developing and maintaining current resources, might provide additional insights into how hospitals leverage their marketing budgets.

Future research may also want to address the response bias, selection bias, and common method bias from which this type of survey research may suffer. For example, our measure for advertising influence was fairly skewed to the positive, which may explain its positive influence on other intermediate variables. Finally, while our study finds the importance of marketing in the value-creation process for hospitals in California and Washington, the smaller, regional nature of the sample may limit the generalizability of the study. Our findings should be interpreted based on a restricted sample that may not be representative of the population. Future research might test this model using a larger national sample that also addresses the potential effect of common method bias.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jbusres.2019.09.037.

References

Aaker, D. A. (1996). *Building strong brands.* Simon and Schuster.

Alonso, J. M., Clifton, J., & Díaz-Fuentes, D. (2015). The impact of New Public Management on efficiency: An analysis of Madrid's hospitals. *Health Policy, 119*(3), 333–340.

Al-Refaie, A., Fouad, R. H., Li, M.-H., & Shurrab, M. (2014). Applying simulation and DEA to improve performance of emergency department in a Jordanian hospital. *Simulation Modelling Practice and Theory, 41*, 59–72.

Ambler, T. (2003). *Marketing and the bottom line: Creating the measures of success.* Financial Times/Prentice Hall.

Ambler, T., Kokkinaki, F., & Puntoni, S. (2004). Assessing marketing performance: Reasons for metrics selection. *Journal of Marketing Management, 20*(3–4), 475–498.

Amit, R., & Schoemaker, P. J. (1993). Strategic assets and organizational rent. *Strategic Management Journal, 14*(1), 33–46.

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management science, 30*(9), 1078–1092.

Barney, J. B. (1991). Firm resources and sustained competitive advantage. *Journal of Management, 17*(1), 99–120.

Barney, J. B. (2014). How marketing scholars might help address issues in resource-based theory. *Journal of the Academy of Marketing Science, 42*(1), 24–26.

Barney, J. B., & Arikan, A. M. (2005). The resource-based view: Origins and implications. *The Blackwell Handbook of Strategic Management,* 123–182.

Barney, J. B., & Hesterly, W. S. (2012). *Strategic management and competitive advantage: Concepts* (4th ed.). New Jersey: Pearson.

Butler, T. W., & Li, L. (2005). The utility of returns to scale in DEA programming: An analysis of Michigan rural hospitals. *European Journal of Operational Research, 161*(2), 469–477.

Calantone, R., & Rubera, G. (2012). When should RD & E and marketing collaborate? The moderating role of exploration–exploitation and environmental uncertainty. *Journal of Product Innovation Management, 29*(1), 144–157.

Capraro, A. J., & Srivastava, R. K. (1997). Has the influence of financial performance on reputation measures been overstated? *Corporate Reputation Review, 1*(1), 86–92.

Castelli, A., Street, A., Verzulli, R., & Ward, P. (2015). Examining variations in hospital

productivity in the English NHS. *The European Journal of Health Economics, 16*(3), 243–254.

Chang, H.-H. (1998). Determinants of hospital efficiency: The case of central government-owned hospitals in Taiwan. *Omega, 26*(2), 307–317.

Chang, H., Chang, W.-J., Das, S., & Li, S.-H. (2004). Health care regulation and the operating efficiency of hospitals: Evidence from Taiwan. *Journal of Accounting and Public Policy, 23*(6), 483–510.

Chang, S.-J., Hsiao, H.-C., Huang, L.-H., & Chang, H. (2011). Taiwan quality indicator project and hospital productivity growth. *Omega, 39*(1), 14–22.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research, 2*(6), 429–444.

Chen, A., Hwang, Y., & Shao, B. (2005). Measurement and sources of overall and input inefficiencies: Evidences and implications in hospital services. *European Journal of Operational Research, 161*(2), 447–468.

Chen, Y. C., Li, P. C., Evans, K. R., & Arnold, T. J. (2017). Interaction orientation and product development performance for Taiwanese electronics firms: The mediating role of market-relating capabilities. *Journal of Product Innovation Management, 34*(1), 13–34.

Chiu, Y.-H., & Huang, C.-W. (2011). Evaluating the optimal occupancy rate, operational efficiency, and profitability efficiency of Taiwan's international tourist hotels. *The Service Industries Journal, 31*(13), 2145–2162.

Chiu, Y.-H., Huang, C.-W., & Ma, C.-M. (2011). Assessment of China transit and economic efficiencies in a modified value-chains DEA model. *European Journal of Operational Research, 209*(2), 95–103.

Chiu, Y.-H., Huang, C.-W., & Ting, C.-T. (2011). Measuring the repair performance for stricken cultivated land and agricultural efficiency in China with a modified two-stage DEA model. *Asia-Pacific Journal of Operational Research, 28*(05), 633–649.

Chowdhury, H., Zelenyuk, V., Laporte, A., & Wodchis, W. P. (2014). Analysis of productivity, efficiency and technological changes in hospital services in Ontario: How does case-mix matter? *International Journal of Production Economics, 150*, 74–82.

Clark, B. H. (1999). Marketing performance measures: History and interrelationships. *Journal of Marketing Management, 15*(8), 711–732.

Davcik, N. S., & Sharma, P. (2016). Marketing resources, performance, and competitive advantage: A review and future research directions. *Journal of Business Research, 69*(12), 5547–5552.

Dutta, S., Narasimhan, O., & Rajiv, S. (1999). Success in high-technology markets: Is marketing capability critical? *Marketing Science, 18*(4), 547–568.

Gholami, R., Higón, D. A., & Emrouznejad, A. (2015). Hospital performance: Efficiency or quality? Can we have both with IT? *Expert Systems with Applications, 42*(12), 5390–5400.

Gok, M. S., & Sezen, B. (2013). Analyzing the ambiguous relationship between efficiency, quality and patient satisfaction in healthcare services: The case of public hospitals in Turkey. *Health Policy, 111*(3), 290–300.

Hausman, W. H., Montgomery, D. B., & Roth, A. V. (2002). Why should marketing and manufacturing work together?: Some exploratory empirical results. *Journal of Operations Management, 20*(3), 241–257.

Hitt, M. A., Xu, K., & Carnes, C. M. (2016). Resource based theory in operations management research. *Journal of Operations Management, 41*, 77–94.

Ho, T. H., & Tang, C. S. (2009). Introduction to the special issue on marketing and operations management interfaces and coordination. *Production and Operations Management, 18*(4), 363–364.

Hsieh, L.-F., & Lin, L.-H. (2010). A performance evaluation model for international tourist hotels in Taiwan—An application of the relational network DEA. *International Journal of Hospitality Management, 29*(1), 14–24.

Hsu, Y.-C. (2013). The efficiency of government spending on health: Evidence from Europe and Central Asia. *The Social Science Journal, 50*(4), 665–673.

Huang, C.-W., Ho, F. N., & Chiu, Y.-H. (2014). Measurement of tourist hotels' productive efficiency, occupancy, and catering service effectiveness using a modified two-stage DEA model in Taiwan. *Omega, 48*, 49–59.

Kao, L.-J., Lu, C.-J., & Chiu, C.-C. (2011). Efficiency measurement using independent component analysis and data envelopment analysis. *European Journal of Operational Research, 210*(2), 310–317.

Kazley, A. S., & Ozcan, Y. A. (2009). Electronic medical record use and efficiency: A DEA and windows analysis of hospitals. *Socio-Economic Planning Sciences, 43*(3), 209–216.

Kim, J.-R., Jeon, E.-C., Cho, S., & Kim, H. (2018). The promotion of environmental management in the South Korean health sector—case study. *Sustainability, 10*(6), 2081.

Kotler, P., & Keller, K. L. (2007). *A framework for marketing management.* Pearson.

Kozlenkova, I. V., Samaha, S. A., & Palmatier, R. W. (2014). Resource-based theory in marketing. *Journal of the Academy of Marketing Science, 42*(1), 1–21.

Krasnikov, A., & Jayachandran, S. (2008). The relative impact of marketing, research-and-development, and operations capabilities on firm performance. *Journal of Marketing, 72*(4), 1–11.

Kull, A. J., Mena, J. A., & Korschun, D. (2016). A resource-based view of stakeholder marketing. *Journal of Business Research, 69*(12), 5553–5560.

Lam, S. Y., Shankar, V., Erramilli, M. K., & Murthy, B. (2004). Customer value, satisfaction, loyalty, and switching costs: An illustration from a business-to-business service context. *Journal of the Academy of Marketing Science, 32*(3), 293–311.

Leleu, H., Moises, J., & Valdmanis, V. G. (2014). How do payer mix and technical inefficiency affect hospital profit? A weighted DEA approach. *Operations Research for Health Care, 3*(4), 231–237.

Lin, C.-H., Chiu, Y.-H., & Huang, C.-W. (2012). Assessment of technology gaps of tourist hotels in productive and service processes. *The Service Industries Journal, 32*(14), 2329–2342.

Linna, M., Häkkinen, U., & Magnussen, J. (2006). Comparing hospital cost efficiency between Norway and Finland. *Health Policy, 77*(3), 268–278.

Luo, X., & Homburg, C. (2007). Neglected outcomes of customer satisfaction. *Journal of Marketing, 71*(2), 133–149.

Makadok, R. (2001). Toward a synthesis of the resource-based and dynamic-capability views of rent creation. *Strategic Management Journal, 22*(5), 387–401.

Malhotra, M. K., & Sharma, S. (2002). Spanning the continuum between marketing and operations. *Journal of Operations Management, 20*(3), 209–219.

Mirzaei, A., Gray, D., & Baumann, C. (2011). Developing a new model for tracking brand equity as a measure of marketing effectiveness. *The Marketing Review, 11*(4), 323–336.

Mitropoulos, P., Talias, M. A., & Mitropoulos, I. (2015). Combining stochastic DEA with Bayesian analysis to obtain statistical properties of the efficiency scores: An application to Greek public hospitals. *European Journal of Operational Research, 243*(1), 302–311.

Morgan, N. A. (2012). Marketing and business performance. *Journal of the Academy of Marketing Science, 40*(1), 102–119.

Morgan, N. A., Vorhies, D. W., & Mason, C. H. (2009). Market orientation, marketing capabilities, and firm performance. *Strategic Management Journal, 30*(8), 909–920.

Nason, R. S., & Wiklund, J. (2018). An assessment of resource-based theorizing on firm growth and suggestions for the future. *Journal of Management, 44*(1), 32–60.

Nath, P., Nachiappan, S., & Ramanathan, R. (2010). The impact of marketing capability, operations capability and diversification strategy on performance: A resource-based view. *Industrial Marketing Management, 39*(2), 317–329.

Ng, Y. C. (2011). The productive efficiency of Chinese hospitals. *China Economic Review, 22*(3), 428–439.

O'Neill, L., Rauner, M., Heidenberger, K., & Kraus, M. (2008). A cross-national comparison and taxonomy of DEA-based hospital efficiency studies. *Socio-Economic Planning Sciences, 42*(3), 158–189.

O'Sullivan, D., & Abela, A. V. (2007). Marketing performance measurement ability and firm performance. *Journal of Marketing, 71*(2), 79–93.

Ouellette, P., & Vierstraete, V. (2004). Technological change and efficiency in the presence of quasi-fixed inputs: A DEA application to the hospital sector. *European Journal of Operational Research, 154*(3), 755–763.

Palmatier, R. W., Dant, R. P., Grewal, D., & Evans, K. R. (2006). Factors influencing the effectiveness of relationship marketing: A meta-analysis. *Journal of Marketing, 70*(4), 136–153.

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879.

Porter, M. E. (2008). *Competitive advantage: Creating and sustaining superior performance.* simon and schuster.

Prahalad, C. K., & Hamel, G. (1990). *The core competence of the corporation.* Harvard Business Review79–91.

Puig-Junoy, J. (2000). Partitioning input cost efficiency into its allocative and technical components: An empirical DEA application to hospitals. *Socio-Economic Planning Sciences, 34*(3), 199–218.

Rouyendegh, B. D., Oztekin, A., Ekong, J., & Dag, A. (2016). Measuring the efficiency of hospitals: A fully-ranking DEA–FAHP approach. *Annals of Operations Research,* 1–18.

Rust, R. T., Ambler, T., Carpenter, G. S., Kumar, V., & Srivastava, R. K. (2004). Measuring marketing productivity: Current knowledge and future directions. *Journal of Marketing, 68*(4), 76–89.

Rust, R. T., Lemon, K. N., & Zeithaml, V. A. (2004). Return on marketing: Using customer equity to focus marketing strategy. *Journal of Marketing, 68*(1), 109–127.

Sawhney, R., & Piper, C. (2002). Value creation through enriched marketing–operations interfaces: An empirical study in the printed circuit board industry. *Journal of Operations Management, 20*(3), 259–272.

Sheth, J. N., & Sisodia, R. S. (2002). Marketing productivity: Issues and analysis. *Journal of Business Research, 55*(5), 349–362.

Srivastava, R. K., Shervani, T. A., & Fahey, L. (1998). Market-based assets and shareholder value: A framework for analysis. *Journal of Marketing,* 2–18.

van Ineveld, M., van Oostrum, J., Vermeulen, R., Steenhoek, A., & van de Klundert, J. (2016). Productivity and quality of Dutch hospitals during system reform. *Health Care Management Science, 19*(3), 279–290.

Verhoef, P. C., & Leeflang, P. S. (2009). Understanding the marketing department's influence within the firm. *Journal of Marketing, 73*(2), 14–37.

Vorhies, D. W., & Morgan, N. A. (2005). Benchmarking marketing capabilities for sustainable competitive advantage. *Journal of Marketing, 69*(1), 80–94.

Wang, C.-H., Lu, Y.-H., Huang, C.-W., & Lee, J.-Y. (2013). R&D, productivity, and market value: An empirical study from high-technology firms. *Omega, 41*(1), 143–155.

Wang, H.-M. D., & Sengupta, S. (2016). Stakeholder relationships, brand equity, firm performance: A resource-based perspective. *Journal of Business Research, 69*(12), 5561–5568.

Watcharasriroj, B., & Tang, J. C. (2004). The effects of size and information technology on hospital efficiency. *The Journal of High Technology Management Research, 15*(1), 1–16.

Wei, C.-K., Chen, L.-C., Li, R.-K., & Tsai, C.-H. (2011). Using the DEA-R model in the hospital industry to study the pseudo-inefficiency problem. *Expert Systems with Applications, 38*(3), 2172–2176.

Wei, C.-K., Chen, L.-C., Li, R.-K., Tsai, C.-H., & Huang, H.-L. (2012). A study of optimal weights of Data Envelopment Analysis-Development of a context-dependent DEA-R model. *Expert Systems with Applications, 39*(4), 4599–4608.

Wernerfelt, B. (2014). On the role of the RBV in marketing. *Journal of the Academy of Marketing Science, 42*(1), 22–23.

Wolper, L. F. (2011). *Health care administration: Managing organized delivery systems* (5th ed.). Jones & Bartlett Publishers.

Yang, D.-H. (2010). Analysis of the efficiency of the regional public hospitals using DEA-AR/AHP combined model. *Health Policy and Management, 20*(4), 74–96.

Yang, J., & Zeng, W. (2014). The trade-offs between efficiency and quality in the hospital production: Some evidence from Shenzhen, China. *China Economic Review, 31*, 166–184.

Yu, M.-M. (2010). Assessment of airport performance using the SBM-NDEA model. *Omega, 38*(6), 440–452.

Yu, M.-M., & Lee, B. C. (2009). Efficiency and effectiveness of service business: Evidence from international tourist hotels in Taiwan. *Tourism Management, 30*(4), 571–580.

Yu, M.-M., & Lin, E. T. (2008). Efficiency and effectiveness in railway performance using a multi-activity network DEA model. *Omega, 36*(6), 1005–1017.

Foo Nin Ho is Professor of Marketing at San Francisco State University. His research areas include ethics, health care marketing, ethnic marketing, international business and consumer behavior. His research has been published in the *Journal of the Academy of Marketing Science, Omega, Journal of Healthcare Marketing, Health Marketing Quarterly, Journal of Business Ethics, Journal of Marketing Theory and Practice, Journal of Consumer Marketing, Journal of Promotion Management, Journal of Travel and Tourism Marketing, Social Responsibility Journal* as well as various international and national proceedings.

Chin-wei Huang is an Associate Professor in the Department of Business and Entrepreneurial Management at Kainan University, Taiwan. He specializes in Data Envelopment Analysis (DEA) method in measuring performance in various business areas. His research has been published in journals such *Omega, Service Industries Journal, Journal of the Operational Research Society, Journal of Travel & Tourism Marketing, Journal of Productivity Analysis, European Journal of Operational Research, Cornell Hospitality Quarterly, International Transactions in Operational Research,* among others.