A SATISFICING DEA MODEL TO MEASURE THE CUSTOMER-BASED BRAND EQUITY

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Abstract. Ever since the inception of brand values, these have become a benchmark for many data-driven strategies, eventually providing a basis for vertical/horizontal integrations, as well. In recent decades, brands have become comparable across the industries, based on their value derived either from the customer perception or in terms of the firm financials. Numerous models have been developed in time to measure the customer-based brand equity; nevertheless, they all evaluate brand equity in an absolute sense. The present research paper provides an avenue to measure the customer-based brand equity in a relative sense using a satisficing DEA model. The information for this model has been collected through a customer-based survey questionnaire in line with predefined brand equity dimensions, which have been verified through a confirmatory factor analysis. We demonstrate the approach by means of applying the proposed model to measure the efficiency of cell phone brands.

1. Introduction

The concept of brand equity has emerged out of the belief that a successful brand can help generate more money resulting from higher margins and higher promotional effectiveness [24], contributing, thus, to an increased market share that can translate into a competitive advantage for the company supplying that brand to the market. It is only fair to say, then, that brand equity is ultimately determined by the actual customer [21].

In time, many researchers have contributed to the development of the concept of brand equity, among which the most notable names are Aaker [1], Srivastava and Shocker [71], Kapferer [40], and Keller [42,43]. There is no universally accepted definition of brand equity [44,79]; nevertheless, all the existing conceptualizations of brand equity agree that brand equity represents the value that a brand name adds to a specific product [14,24,81]. Or, in the words of Kotler and Keller ([45], p. 241) "one of the most valuable intangible assets of a firm is its brands, and it is incumbent on marketing to properly manage their value". In line with this stream of thought, it appears justifiable to dedicate efforts to measure the brand equity, which, in turn, would yield valuable knowledge aimed at improving the marketing performance of the respective brand.

This variety of conceptualizations for the construct has been accompanied by the existence of a variety of methodologies to measure the same [16], which can be explained by the fact that since value in itself is not an objective concept, there are many ways of measuring brand value from the customer's perspective [21].

The existent measurement methodologies can be classified into two categories: (a) direct measurements of brand equity, which focus on brand equity outcomes [3, 17, 37] and (b) indirect measurements of brand equity, which focus on measuring the components of brand equity [48, 53, 84]. Nevertheless, they all evaluate an entity with the average performance of a set of similar entities under consideration and, as such, fail to derive implications on how to adjust resources among predefined dimensions to improve the brand equity. It is in this context, then, that research efforts toward the development of a better measurement technique are welcome.

The main purpose of the present paper is to measure the customer-based brand equity efficiency to identify efficient brands versus inefficient brands in terms of customer perception. The present research paper represents, thus, a novel attempt to develop a satisficing DEA model to measure the customer-based brand equity efficiency under a stochastic environment that is, furthermore, free from any theoretical distributional assumptions. The proposed model is then applied to measure the efficiency of nine major cell phone brands based on the data collected through a survey questionnaire.

The remainder of the paper unfolds as follows: the subsequent sub-sections elaborate on the concept of brand equity, its components, and the existing measurement methodologies. The next section introduces the DEA methodology along with the formulation of the stochastic DEA model. Subsequently, a description of the data used and empirical findings obtained is provided. Finally, the paper concludes with limitations of the current study and insights for future research on the topic.

1.1. The concept of brand equity

The birth of the concept of branding can be dated centuries back, to the times when the brick-makers in ancient Egypt and the members of the trade guilds in the medieval Europe used to differentiate their merchandise on the market by placing unique symbols on their products. The term of "brand" as such was officially coined in the 16th century, when whiskey distillers in Scotland started burning the name of the producer onto each barrel in an attempt to not only trace the product to its respective origin, but also to avoid its replacement with cheaper versions [24]. The definition of brand equity has not changed much since 1988 when it was defined by Leuthesser as "the added value with which a given brand endows a product" [49], or later on, in 1993, by Keller as "marketing effects uniquely attributable to the brand... when certain outcomes result from the marketing of a product or service because of its brand name that would not occur if the same product or service did not have that name" ([42], p. 1).

As such, referring to professional service firms, Byron [9] stated that brand equity is market-based assets (customer loyalty, brand/corporate image, customer awareness, secured distribution, and relationships with customers/distributors). Lassar *et al.* ([48], p. 1) highlighted that brand equity stems from the greater confidence that customers place in a brand than they do in its competitors. Aaker ([1], as cited by [17]) defined brand equity as the "added value that a brand name gives to a product". Further, a group of experts described brand equity as "the ensemble of associations and behaviors that permit branded products to achieve greater sales volumes and greater profit margins than they would have been able to achieve without the brand name" ([35], p. 290). Finally, Fetscherin and Toncar ([27], p. 135) conceptualized brand equity as the "intrinsic value that a brand adds to the tangible product or service".

It is relevant to highlight that the idea of brand equity is not restricted to products. Of course with products the objective is to minimize the cognitive effort or to add symbolic value. In the case of services, the previous reasons might also apply but "because of the distinct nature of professional services, brand equity is more likely to occur because customers need a way to reduce risk and to assess quality" ([9], p. 11).

The power of brand equity is that by being present in a product/service, it might change the customers' perception of the product/service and, thus, might also change their purchasing behavior. Brand equity research has been studied from two different but complementary perspectives: one based on its financial impact and the other (which will be, furthermore, adopted in this paper) based on its strategic impact on the improvement of marketing productivity. The latter is generally called customer-based brand equity (CBBE).

1.2. The customer-based brand equity

CBBE has been defined in many ways: as the "differential effect of brand knowledge on customer response to the marketing of the brand" ([36], as cited in [48], p. 12; [42], p. 2), as the "overall utility that the customer associates to the use and consumption of the brand; including associations expressing both functional and symbolic utilities" ([79], p. 28), and as "a set of perceptions, attitudes, knowledge, and behaviors on the part of the customers that results in increased utility and allows a brand to earn greater volume or greater margins that it could without the brand name" ([16], p. 48).

Furthermore, Feldwick ([26], p. 87) distinguished three dimensions of brand equity: one related to finance ("the total value of a brand as a separable asset") and the other two focused on the customer ("a measure of the strength of the customer's attachment to a brand" and "a description of the associations and beliefs the customer has about the brand").

The challenge, then, would be to build a strong brand, sustain its growth over time, and expand the business by leveraging the brand ([24], p. 24). Farquhar [24] further suggested that in order to build a strong brand, firms needed to do three things: create positive brand evaluations, create accessible brand attitudes, and keep a consistent brand image. Aaker and Keller [2] stated that for leveraging the brand into brand extensions one has to evaluate the perceived quality of the original brand and the relationship or "fit" between the original and the extension product classes and that inferred attributes beliefs both enhance and harm the evaluation of a brand extension.

1.3. The components of the customer-based brand equity

Farquhar [24] recognized three elements for building a strong brand: positive brand evaluations, accessible brand attitudes, and consistent brand image. However, he did not elaborate further on how to measure any of them. Keller [42] developed a model to explain the brand knowledge consisting of two main dimensions: brand awareness and brand image. He defined brand awareness as the "strength of the brand node or trace in memory, as reflected by customers' ability to identify the brand under different conditions" (p. 3) with two components: brand recall and brand recognition. As previously mentioned, Aaker and Keller [2] studied the potential success of brand extension based on how the customer perceived the quality of the original brand and the relationship of "fit" between the original and the extension product classes. Subsequently, Keller ([42], p. 12) went further to explain two basic approaches to measuring CBBE: the indirect approach through measuring the brand knowledge (brand awareness and brand image) and the direct approach through assessing the impact of brand knowledge on customer response to different elements of the firm's marketing program. The indirect approach uses a combination of surveys and focus groups, whereas the direct approach uses experiments (with the "blind" test as the main activity under this approach).

1.4. Models to measure the customer-based brand equity

Many research efforts have been directed toward measuring the brand equity [58]. Lassar *et al.* [48], for example, developed a model with five components: performance, social image, value, trustworthiness, and attachment; Cobb-Walgren, Ruble, and Donthu [17], building upon Aaker [1], defined three main components: awareness,

brand associations, and perceived quality to measure brand equity; Yoo and Donthu ([83], as cited by [80]), developed two distinct brand equity scales: an overall brand equity scale using a set of four items and a multi-dimensional brand equity scale.

Keller [42] depicted a model to measure the CBBE based on brand knowledge, which is in turn composed of two main items: brand awareness (recall and recognition) and brand image (types of associations, favorability of associations, the strength of associations, and uniqueness of associations). He called this model an indirect approach to measuring the brand equity. He also went further to identify a direct approach to measuring the CBBE by means of directly measuring the effects of brand knowledge on customer response to marketing for the brand (using experiments).

Park and Srinivassan [58] developed a survey-based model to measure brand equity in a product category and evaluate the equity of the brand's extension into a different but related product category. Moreover, this method needs two sets of data: one data set which provides objectively measured attribute levels of different brands in a given product category (laboratory tests, blind customer tests, or expert evaluations) and the second data set which is survey-based and is collected from a random sample of current users of the product category (overall preference ratings, preference structure measurements, and attribute perception ratings).

Lassar *et al.* [48] defined five dimensions to measure the brand equity: performance (a customer's judgment about a brand's fault-free and long lasting physical operation and flawlessness in the product's physical construction), social image (the customer's perception of the esteem in which the customer's social group holds the brand), commitment or attachment (the relative strength of a customer's positive feelings towards the brand), value (the perceived brand utility relative to its costs assessed by the customer), and trustworthiness (the confidence a customer places in the firm and the firm's communications, and as to whether the firm's actions would be in the customer's interest).

Cobb-Walgren *et al.* [17] developed an operationalization of the brand equity measurement using two parts: one that measured the brand equity using the perceptual components of Aaker's [1] definition; and a second that measured the brand preferences and usage intentions (using conjoint questions), while Vazquez *et al.* [79] developed a model to measure the brand equity based on the value ascribed to the brands by the customers themselves, using four basic dimensions: product functional utility (measured by comfortability, safety, and duration), product symbolic utility (measured by aesthetics), brand name functional utility (measured by guarantee), and brand name symbolic utility (measured by social identification, status, and personal identification).

Silverman *et al.* [68] developed a two-study research endeavor, the first of which related brand awareness to market outcomes and the second that related brand image to market outcomes. The first study combined two types of measurement on 19 product categories: one being customer-based measures (brand familiarity, brand usage, and brand favorability) and the second one being market-based measures (sales and brand valuation figures). The second study examined the relationships between category position and brand image measuring favorability, uniqueness, and strength of brand associations.

Some studies have been developed to include additional aspects related to brand equity, such as is effect on durable goods, price, and risk. Rajasekar and Nalina [60] developed a study on durable goods using the measurement dimensions of Lassar *et al.* [48] and found that all of the five dimensions (performance, social image, value, trustworthiness, and attachment) were important to the customers. Moreover, they reported that if a brand failed on a single dimension, then customers would not evaluate the other dimensions highly. Fetscherin and Toncar [27] developed a model of brand equity in which they included the effect of price. They found that the model explained a large percentage of the variance of the price set by the manufacturers and paid by the customers of various brands of sedan car models in Germany and that the different independent variables used appeared to have significant effects on the prices. Furthermore, Rego, Billet, and Morgan [61] related brand equity with firm risk, concluding that the evaluation of a firm's risk by individuals might be modulated by the firm's brand equity. He stated that "when firm risk was reduced, the value of the firm's cash flows increased even if their level remained exactly the same" (p. 55).

2. Formulation of the satisficing DEA model

Built upon the seminal works of Debreu [22], Shephard [67], and Farrell [25], and popularized by Charnes, Cooper, and Rhodes [13], the DEA methodology has evolved in time to become one of the most powerful management science tools in the hands of both practitioners and researchers, with applications in almost every field [11]. One of the great advantages resides in the very fact that it is a nonparametric approach, which means it allows estimating production frontiers and evaluating the relative efficiency of the DMUs by incorporating multiple inputs and multiple outputs without any assumption on the functional form. Nevertheless, it also requires the input and output data to be constant. As such, in a context in which in reality many observations are stochastic in nature, conventional DEA has been criticized for not allowing stochastic information to be incorporated in input and output data (such as data entry errors or measurement errors), which may, in turn, lead to the DEA efficiency measures to be sensitive to such variations in the information [77].

To address such shortcomings, Sengupta [72] incorporated variations in both inputs and outputs by generalizing the CCR (Charnes–Cooper–Rhodes) ratio model by defining the measure of efficiency of a DMU as the maximum of the sum of the expected ratio of weighted outputs to weighted inputs and a reliability function subject to several chance constraints. The works of Banker [4, 5], Sengupta and Sfeir [66], Huang and Li [33], Cooper *et al.* [20], Li [50], Sueyoshi [72], Huang and Li [34], Hall and Simar [30], and Simar [69] represent other notable contributions to the stochastic DEA literature to which the interested reader can turn for additional insights. Another approach to stochastic DEA is chance-constrained programming, adopted by Sengupta [65], Desai and Schinnar [23], Land *et al.* [46], Olesen and Petersen [56], Olesen [55], and Talluri *et al.* [73], among others, who introduced chance-constrained formulations to derive efficient frontiers that consider both statistical noise and measurement errors. A detailed review on the topic of stochastic DEA can be found in Olesen and Petersen [57].

DEA aims to identify the most efficient DMU among all DMUs and to estimate the relative efficiency of the DMUs. Consider a set of n brands, each consuming different amounts of a vector of inputs, $x_j = (x_{1j}, x_{2j}, \ldots, x_{mj})^T$ to produce a vector of outputs $y_j = (y_{1j}, y_{2j}, \ldots, y_{mj})^T$. The superscript T represents the transpose. The DMU to be evaluated is designated as DMU_0 and its input-output vector is denoted as (x_0, y_0) The output-oriented Banker–Charnes–Cooper (BCC) model, in line with Banker *et al.* [6], can be defined as follows:

$$\text{Max } \phi$$

subject to

$$\sum_{j=1}^{n} y_{rj}\lambda_j \geq \phi y_{r0}, \quad r = 1, 2, \ldots, s,$$

$$\sum_{j=1}^{n} x_{ij}\lambda_j \leq x_{i0}, \quad i = 1, 2, \ldots, m,$$

$$\sum_{j=1}^{n} \lambda_j = 1,$$

$$\lambda_j \geq 0, \quad j = 1, 2, \ldots, n, \tag{2.1}$$

where the contraction factor ϕ exceeds unity, $\phi \geq 1$. The efficiency is the reciprocal of the contraction factor ϕ, *i.e.*, $1/\phi(= \varphi)$. Here, λ_j represents the structural variables.

Lovell and Pastor [51] proposed radial DEA models without inputs (or without outputs), and radial DEA models with a single constant input (or with a single constant output) so as to accommodate situations that arise

in few multi-criteria decision-making problems, wherein there is no negative (or positive) evaluation item. A BCC model without inputs in line with Lovell and Pastor [51] can be defined as follows:

$$\text{Max } \phi$$

subject to

$$\sum_{j=1}^{n} y_{rj}\lambda_j \geq \phi y_{r0}, \quad r = 1, 2, \ldots, s,$$

$$\sum_{j=1}^{n} \lambda_j = 1,$$

$$\lambda_j \geq 0, \quad j = 1, 2, \ldots, n. \tag{2.2}$$

The objective of the problem is to maximize the radial expansion of the vector of the dimension-wise CBBE for the brand being evaluated. The constraints of the problem restrict this expansion to a convex combination of the dimension-wise CBBE of the other brands under study. Stochastic variation is very common in CBBE; it could be due to measurement or specification errors. Here, we then permit some stochastic variation around the efficiency frontier, so as to make the model to accommodate the said errors.

Charnes and Cooper [12] first proposed a chance-constrained programming to measure the efficiency in the case of uncertainty and then analyzed the cases of the possibility of violated constraints. Thore [74], Banker [5], and Land, Lovell, and Thore [46, 47] made efforts to address data uncertainty in terms of stochastic variation in DEA. To accommodate the stochastic variation, we modify our constraint equations in model (2.2) and add the mechanism of the chance constraints introduced by Land, Lovell, and Thore [46]. Thus, the corresponding chance-constrained efficiency measure is calculated as:

$$\text{Max } \phi$$

subject to

$$Pr\left[\sum_{j=1}^{n} \tilde{y}_{rj}\lambda_j \geq \phi\tilde{y}_{r0}\right] \geq 1 - \alpha_r, \quad r = 1, 2, \ldots, s,$$

$$\sum_{j=1}^{n} \lambda_j = 1,$$

$$\lambda_j \geq 0, \quad j = 1, 2, \ldots, n. \tag{2.3}$$

Here, "Pr" means probability and "$\sim$" identifies these inputs as random variables with known probability distributions. The chance constraints indicate that the probability of the observed output dimension-wise CBBE to exceed the best practice output dimension-wise CBBE should be of at least level $1 - \alpha_r$, $\forall r$. We assume that dimension-wise CBBE is stochastically independent; the equity-based performance of one brand is independent of that of another brand.

Cooper et al. [19] incorporated Simon's [70] satisficing concepts into DEA models with chance constraints in order: (i) to effect contact with theories of behavior in social psychology, as well as (ii) to extend the potential uses of DEA models to cases where 100% efficiency can be replaced by aspired levels of performance. In line with Udhayakumar et al. [77], Charles and Kumar [11], Tsolas and Charles [76] and with the support of the above

literature, the P-model chance-constrained DEA with "satisficing" concept can be defined for model (2.3) as follows:

$$\text{Max } \Pr(\phi \geq \beta^{-1})$$

subject to

$$\Pr\left[\sum_{j=1}^{n} \tilde{y}_{rj}\lambda_j \geq \phi\tilde{y}_{r0}\right] \geq 1 - \alpha_r, \quad r = 1, 2, \ldots, s,$$

$$\sum_{j=1}^{n} \lambda_j = 1,$$

$$\lambda_j \geq 0, \quad j = 1, 2, \ldots, n. \tag{2.4}$$

Here, "Pr" and "$\sim$" are as defined above and one can interpret β as an aspiration level either imposed by the firms or by the board members or by any relevant agency which measures the CBBE. It is to be noted that in model (2.4) the aspiration level is only imposed to the objective function and not at the constraint level, meaning that the aspiration level at the constraint level is fixed at 100%.

Definition 2.1.
If $\beta = 1$, DMU_0 is called stochastically efficient if and only if $\Pr(\phi \geq \beta^{-1}) = \alpha_0$ or $\Pr(\varphi \leq \beta) = \alpha_0$.

Definition 2.2.
If $\beta < 1$, DMU_0 is called satisficing-efficient if and only if $\Pr(\phi \geq \beta^{-1}) = \alpha_0$ or $\Pr(\varphi \leq \beta) = \alpha_0$.

2.1. Stochastic simulation

Let us consider the chance constraints discussed in model (2.4) and employ the stochastic simulation technique provided by Rubinstein [62], in line with Udhayakumar *et al.* [77], Charles and Kumar [11], and Tsolas and Charles [76]:

$$\Pr\left[\sum_{j=1}^{n} \tilde{y}_{rj}\lambda_j \geq \phi\tilde{y}_{r0}\right] \geq 1 - \alpha_r, \quad r = 1, 2, \ldots, s \tag{2.5}$$

Let $\psi_r(\tilde{y}_r, \lambda) = \sum_{j=1}^{n} \tilde{y}_{rj}\lambda_j - \phi\tilde{y}_{r0}$.

Then, the chance constraint can be represented as:

$$\Pr[\psi_r(\tilde{y}_r, \lambda) \geq 0] \geq 1 - \alpha_r, \quad r = 1, 2, \ldots, s \tag{2.6}$$

where $\tilde{y}_r = (\tilde{y}_{r1}, \tilde{y}_{r2}, \ldots, \tilde{y}_{rn})$ is the amount of outputs that the random vector utilized and $\lambda = (\lambda_1, \lambda_2, \ldots, \lambda_n)$ is the factor of structural variables associated with the respective brands. Each $\tilde{y}_{rj}$ has an empirical distribution derived from the existing data set. Then, the N independent random vectors for each $\tilde{y}_r$ are generated in accordance with the empirical distribution, as follows: $\tilde{y}_r^{(k)} = (\tilde{y}_{r1}^{(k)}, \tilde{y}_{r2}^{(k)}, \ldots, \tilde{y}_m^{(k)})$, $k = 1, 2, \ldots, N; r = 1, 2, \ldots, s$. Let $N_r^0(\leq N), r = 1, 2, \ldots, s$ be the number of times the following relation satisfies: $\psi_r(\tilde{y}_r, \lambda) \geq 0, r = 1, 2, \ldots, s$; then, by the definition of the chance constraint, (2.6) and, hence, (2.5) hold if $N_r^0/N \geq 1 - \alpha_r, r = 1, 2, \ldots, s$.
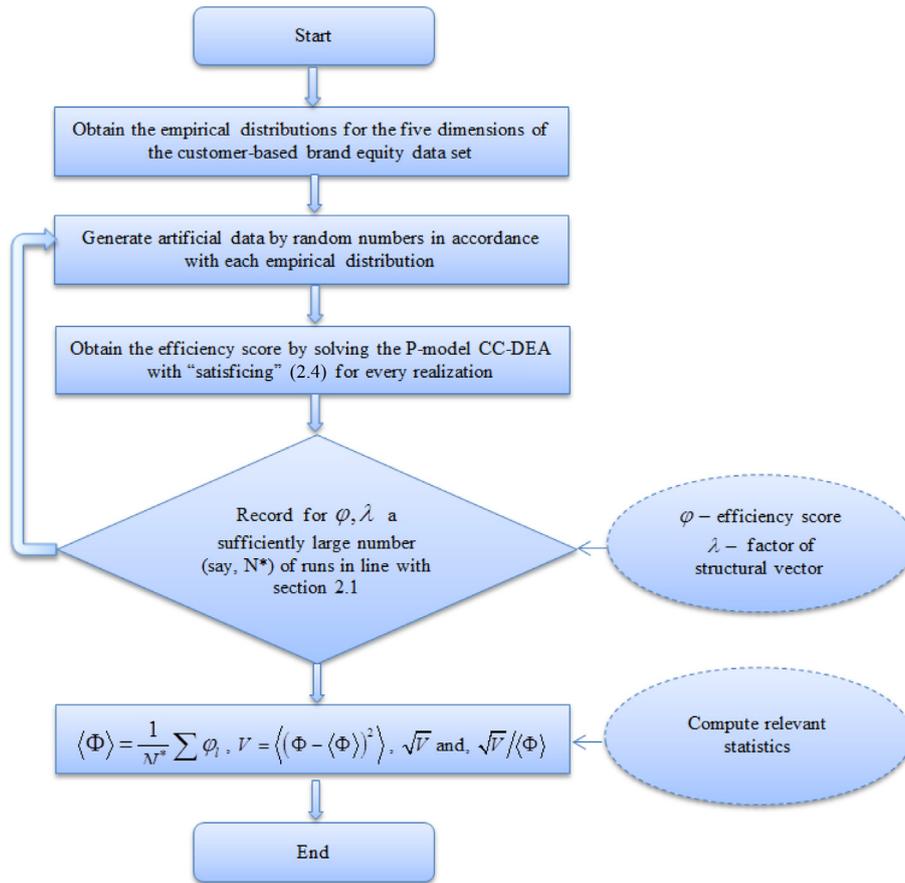
FIGURE 1. Monte Carlo simulation algorithm and relevant metrics.

In a similar line, one can handle a stochastic objective constraint, too. Figure 1 depicts the flow of the Monte Carlo simulation algorithm and relevant metrics.

For any DMU of interest, let $\varphi_1, \varphi_2, \ldots, \varphi_{N^*}$ be the efficiency scores for N^* runs; let $\lambda^{(1)}, \lambda^{(1)}, \ldots, \lambda^{(N^*)}$, be the factor of structural vectors for N^* runs, and let $\eta(.)$ be the count-if function, which provides the number of times the criterion is satisfied. One can define *expectation of efficiency scores* as $\langle \Phi \rangle = \lim_{N^* \to \infty} \frac{1}{N^*} \sum_l \varphi_l$, *variance of efficiency scores* as $\sqrt{V} = \langle (\Phi - \langle \Phi \rangle)^2 \rangle$, *standard deviation* and *coefficient of variation of efficiency scores* as $\sqrt{V}$ and $\langle \Phi \rangle^{-1} \sqrt{V}$, respectively.

The probability of DMU$_0$ being efficient can be defined as:

$$P_0 = (N^*)^{-1} \eta(\phi_l = 1, \forall l) = (N^*)^{-1} \eta(\varphi_l = 1, \forall l) \qquad (2.7)$$

and the probability of DMU$_0$ being efficient at most at the given aspiration level β is:

$$P_\beta = (N^*)^{-1} \eta(\phi_l \geq \beta^{-1}, \forall l) = (N^*)^{-1} \eta(\varphi_l \leq \beta, \forall l) \qquad (2.8)$$

The probability of the DMU being in the reference set is computed as:

$$P_{\lambda_j} = \eta \left(\lambda_j^{(l)} > 0, \forall l \right) \left\{ \sum_{j=1}^{n} \eta(\lambda_j^{(l)} > 0, \forall l) \right\}^{-1}, \quad j = 1, 2, \ldots, n \tag{2.9}$$

3. An application to cell phone customer-based brand equity

3.1. CBBE instrument

A survey was conducted in order to measure the cell phone users' determinants of brand equity. As such, a structured questionnaire based on the literature reviewed was applied as an instrument of data collection.

The initial step consisted, thus, in reviewing the published research studies relevant to our work. It is important to highlight that the present paper builds upon the work undergone by Tong and Hawley [75], to which the interested reader can refer for more information.

The survey questionnaire consisted of items measuring the dimensions of brand equity, as well as it included demographic profile questions, such as those related to age, gender, educational qualification, job sector, and monthly income. The identified variables measuring the dimensions of brand equity were included into a questionnaire in the form of 18 positively worded statements. The respondents were asked to rate each of the 18 statements using a 10-point Likert scale that varied from 1 – representing that the respondent strongly disagreed with the situation described – to 10 – representing that the respondent strongly agreed with the situation described. Moreover, all of the 18 statements were reshuffled to make sure that the questions related to the same dimension were not grouped together.

The questionnaire was originally developed in English; nevertheless, to facilitate a better understanding of the variables, it was furthermore translated into Spanish, and then back-translated into English by two subject experts in the field in order to ensure its soundness.

A pilot study conducted on 36 respondents before the actual empirical approach indicated a positive gesture with regard to the face validity of the instrument, which encouraged us to proceed with further analysis.

3.2. Sampling framework and sample size

The sampling units for the present study consisted of cell phone users in the city of Metropolitan Lima, Peru. The population in this region has access to all kinds of cell phone brands and, thus, can be considered to be representative of the target population for the assessment of the determinants of brand equity in Peru.

As such, the questionnaires were administered in and around the following four Commercial Shopping Centers, where the monthly flow of people is considered to be higher than in any other region of Lima: Mega Plaza Cono Norte, Plaza San Miguel, Jockey Plaza, and La Rambla San Borja. As such, participants were selected based on probability and non-probability sampling from these four Commercial Shopping Centers. The sample size in each stratum was allocated proportionately to the population size (considered, in our case, to be the monthly number of visitors) of the stratum. Table 1 exhibits detailed information with regard to the sampling plan. Furthermore, for each stratum, convenient sampling was used to obtain the desired information.

For the given time and budget constraints, it was possible to collect only 650 samples. Nevertheless, of the questionnaires collected, 10% were considered unusable because of insufficient data or inconsistencies in the participants' responses, and were, therefore, removed. This filtering yielded a final sample of 585 valid questionnaires, consisting of 207, 181, 164, and 33 participants from Mega Plaza Cono Norte, Plaza San Miguel, Jockey Plaza, and La Rambla San Borja, respectively.

The respondents were requested to participate in the survey when they were found unengaged in other activities; moreover, they were told that their participation was voluntary, confidential, and anonymous, and that the data being collected would be used for academic research purposes only.

TABLE 1. Sampling plan.

S. No.	Name of stratum (Commercial Shopping Center)	Visitors per month	Proportion	S1	S2
1	Mega Plaza Cono Norte*	3 200 000	0.3596	234	207
2	Plaza San Miguel*	2 700 000	0.3034	197	181
3	Jockey Plaza*	2 500 000	0.2809	183	164
4	La Rambla San Borja**	500 000	0.0562	36	33
		8 900 000	1	650	585

Note: * Information provided by LaRepublica.pe available at http://www.larepublica.pe/12-10-20127los-tres-centros-comerciales-con-la-mayor-facturacion-anual-en-el-peru, ** approximate estimation: S1 – Sample size in each stratum, S2 – Sample size in each stratum, after the removal of the invalid questionnaires.

3.3. The data

Following the analysis of the data collected, it was determined that 44% of the respondents were females and 56% were males. The respondents' level of education was primarily university level (59%), followed by the post-graduate education level (25%) and the technical education level (12%). The sectors in which the respondents worked were services (34%), followed by trade and distribution (14%), construction (10%), and mining (10%). Still, 34% of the respondents marked other industries that were not specified in the questionnaire. With regard to income, the respondents reported a monthly income primarily between 3000 and 8000 Peruvian Nuevos Soles (48%), followed by 37% who stated an income between 8000 and 12 000 Peruvian Nuevos Soles, and 30% who stated an income of less than 3000 Peruvian Nuevos Soles per month. Only 5.5% of the respondents stated an income above 12 000 Peruvian Nuevos Soles per month.

With regard to the handset's brand owned by the respondents, 17.6% reported to own a Motorola, followed by HTC (14.7%), Sony (13.5%), Nokia (11.8%), Apple (11.5%), Nextel (10.3%), Samsung (8.9%), LG (6.7%), and Blackberry (5.1%).

3.4. Inputs-outputs under a DEA framework for customer-based brand equity

Unlike the conventional production function approach, where the production process is well defined, the identification of inputs–outputs in the study of CBBE is unclear. Thus, the current study considers the 10-point Likert scale on each dimension as the outputs without taking into consideration any inputs in the DEA model.

In DEA, efficiency scores are sensitive to sampling variations, particularly when small samples are used. Furthermore, when the sample size (number of observations or DMUs) is limited compared to the number of inputs and outputs, an upward bias is present due to dimensionality issues [85]. Regarding the number of DMUs, there are two prevalent views in the existing literature. On the one hand, Golany and Roll [29] and Homburg (2001) suggested that the number of DMUs should be at least twice the number of inputs and outputs, while Nunamaker [54] and Raab and Lichty [59] suggested that there should be at least three times the number of DMUs as there are inputs and outputs. On the other hand, Cook *et al.* [18] pointed out that whereas in statistical regression analysis, sample size is a vital issue – as it tries to estimate the average behaviour of a set of DMUs, – when used as a benchmarking tool, DEA focuses on the performance of each DMU, and as such, the sample size or the number of DMUs being evaluated may be immaterial.

In this study, with an initial total of 9 DMUs with 18 outputs, we can immediately see that the above-mentioned condition is not satisfied. However, as stated by Cook *et al.* [18], this should not constrain a possible DEA-based approach. Generally, survey data involves the existence of a large number of items (questions), which can be multiple times the number of DMUs; but, as it is consumer perception data, one can attempt

to strike a balance between the above two views by means of compressing the number of outputs through a variable reduction technique. A reduction technique, namely, factor analysis, was employed in the present study to confirm the data for patterns and reduce the number of items into a fewer number of factors (constructs) that would constitute our derived outputs. This technique confirmed the existence of five factors for the brands under consideration: perceived quality, brand awareness, brand association, brand loyalty, and overall brand perception. As such, with a total of 9 DMUs with 5 outputs, we ended up with a reasonably better number of outputs for the sample size.

4. Empirical findings

4.1. First-stage empirical findings

As previously mentioned, the instrument was developed based on the existent literature and incorporated an initial of 18 variables. Three items were included for perceived quality (PQ), three items for brand awareness (BAW), four items for brand association (BAS), five items for brand loyalty (BL), and three items for overall brand perception (OBP).

In order to test the multidimensionality of the CBBE construct, a confirmatory factor analysis was run. The hypothesized structure with the loadings for the model is shown in the below Figure 2. It is to be noted that five out of the 18 variables were expelled from their corresponding constructs due to their lack of confirmatory power.
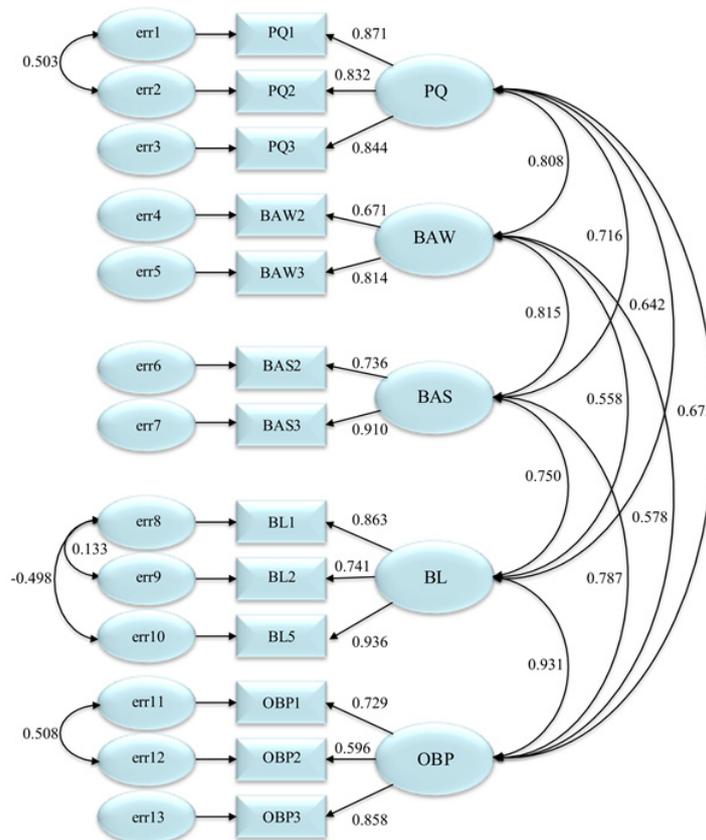

Figure 2. Confirmatory factor analysis model.

Looking at the below Table 2, we notice that the value of chi-square divided by the degrees of freedom is less than 5 [63], the GFI is higher than 0.9 [8], the NFI is higher than 0.9 [8], the CFI is higher than 0.9 [8], the TLI is higher than 0.9 [32], the RMSR is less than 0.05 [32], and the RMSEA has a value very close to the acceptable value of 0.08 or less [7].

A discriminant validity test has been conducted for every pair of factors. The test details have been provided in Table 3. It is evident from the t-values that there is no significant relation between any pair of factors. Hence, the proposed CFA model passes the discriminant validity test.

TABLE 2. Goodness-of-fit measure for the estimated model.

Goodness-of-fit measure	Baseline model	Estimated model	Benchmark
Absolute fit measure			
Likelihood-ratio chi-square(χ^2)	1159.628	232.723	
Degrees of freedom	125	51	
CMIN/DF	9.277	4.563	<5
Non-centrality parameter (NPC)	1034.628	181.723	
Goodness-of-fit index (GFI)	0.801	0.941	$\geq$0.90
Root mean square residual (RMSR)	0.061	0.038	$\leq$0.05
Root mean square error of aproximation (RMSEA)	0.119	0.078	$\leq$0.10
Expected cross-validation index (ECVI)	2.143	0.535	
Incremental fit measure			
Adjusted goodness of fit index (AGFI)	0.728	0.894	$\geq$0.80
Tucker-Lewis index (TLI) or (NNFI)	0.847	0.948	$\geq$0.90
Normed fit index (NFI)	0.862	0.957	$\geq$0.90
Comparative fit index (CFI)	0.875	0.966	$\geq$0.90

TABLE 3. Discriminant validity.

Constructs			t-stat	p-value
PQ	$\leftrightarrow$	OBP	-10.2	0.000
PQ	$\leftrightarrow$	BAW	-6.6	0.000
PQ	$\leftrightarrow$	BAS	-9.8	0.000
PQ	$\leftrightarrow$	BL	-11.9	0.000
OBP	$\leftrightarrow$	BAW	-10.0	0.000
OBP	$\leftrightarrow$	BAS	-7.6	0.000
OBP	$\leftrightarrow$	BL	-3.5	0.000
BAW	$\leftrightarrow$	BAS	-6.2	0.000
BAW	$\leftrightarrow$	BL	-11.6	0.000
BAS	$\leftrightarrow$	BL	-9.6	0.000

Given, thus, that all the fit measures analyzed indicated an acceptable level fit for the proposed model and that the model passed the discriminant validity test, it was decided to provisionally accept the five-dimension brand equity model. These five dimensions (also known as latent constructs, constructs, or factors) were further

employed as outputs in our DEA model by means of considering the weighted average of the items of the specific dimensions, which is discussed in the second-stage empirical findings section.

As can be appreciated in Table 4, there are five dimensions in which the interviewees ranked their responses: perceived quality, brand awareness, brand association, brand loyalty, and overall brand perception, all of whose values are shown by brand: mean value and standard deviation. There are some results that stand out immediately. First, the brand with the highest overall brand perception is Apple (21.612) and the brand with the lowest brand perception is Nokia (16.087). Those results contrast deeply with those brands' market shares in Peru [10] that were reported as follows: Samsung with 43.0% market share, followed by Blackberry with 16%, Sony-Ericsson with 9.9%, Nokia with 9.2%, LG with 8.8% and, finally, Apple with less than 1%. Although from a marketing perspective, corporate strategies might differ among incumbents between market share and profitability, it is important to note that according to an article in the New York Times [15], Apple is capturing 93% of the handset industry profits despite its low market share.

TABLE 4. Summary of CBBE data.

DMU	Name of the brand	n	Perceived quality	Brand awareness	Brand association	Brand loyalty	Overall brand perception
1	Apple	67	25.522 (3.212)	15.881 (3.203)	14.180 (2.801)	21.657 (5.056)	21.612 (5.190)
2	Blackberry	30	18.333 (5.898)	11.967 (2.785)	10.700 (4.203)	14.433 (7.224)	16.433 (7.219)
3	HTC	86	21.023 (5.097)	13.837 (3.457)	12.802 (3.497)	15.686 (6.377)	16.547 (5.517)
4	LG	39	21.513 (3.790)	13.436 (3.485)	11.821 (3.663)	14.385 (4.688)	16.256 (3.871)
5	Motorola	103	23.369 (3.608)	14.330 (3.194)	12.495 (3.322)	16.884 (6.038)	17.019 (5.111)
6	Nextel	60	22.333 (5.164)	14.667 (3.388)	12.767 (3.877)	17.083 (6.995)	17.850 (6.509)
7	Nokia	69	21.870 (4.452)	14.203 (3.592)	11.435 (3.398)	14.406 (5.157)	16.087 (4.987)
8	Samsung	52	25.124 (3.567)	16.808 (2.787)	14.077 (3.667)	20.577 (6.470)	21.212 (5.493)
9	Sony	79	24.494 (3.320)	15.962 (2.345)	14.127 (3.443)	17.684 (6.209)	18.848 (5.442)

Note: The values within the parentheses represent standard deviations.

Second, if we analyze the other CBBE components column by column in Table 4, one can notice that for the Perceived Quality component, the highest value belongs to Apple (25.522) and the lowest to Blackberry (18.333). This appears to show that although Apple ranks first in quality and Blackberry ranks last, the real usage of those brands by customers is influenced by the relationship between the disposable income and the price of the device. For Perceived Quality, three brands are quite close together: Apple, Samsung, and Sony (with values above 24.500), with equal similar standard deviation values. Next, come the rest of the brands (with values between 21.000 and 23.000) except for Blackberry, which ranks last (with a value of 18.333). The influence of smartphones' growth in the Peruvian market might explain that Perceived Quality relates to technology.

As a matter of fact, a study undergone by Kantar Worldpanel [39] showed that, in relation to the amount of pre-purchase research done by customers, those looking to buy an Apple iPhone model are the ones doing the least amount of pre-purchase research, arguably because of a high-perceived quality.

The pervasive influence of the Android operating system for mobile phones in the world (it holds around 88% of the global market) also has a certain impact on the Latin American markets and on the Peruvian market, in particular. That appears to explain why Samsung has 16.808 for Brand Awareness (which is the highest value), followed by Sony (with 15.962) and Apple (with 15.881), with Blackberry (with 11.967) coming in the last place. For Brand Awareness, the same three brands are close together again: Apple, Samsung, and Sony (with values above 15.800) and with equal similar standard deviation values. Next, come the rest of the brands (with values between 13.400 and 14.700) except for Blackberry, which is alone in the last place (with 11.967). Brand Awareness might also be tied to the word of mouth communication. In this regard, Kawakami and Parry [41] conducted a study linking the word of mouth effect among adopters of smartphones with the perceived credibility of product information, perceived availability of complementary products, and the perceived size of the local adopter population. Brand Awareness for Apple products might be, therefore, linked to the high level of word of mouth information from the Apple users. Wollenberg and Thuong [82] also found a positive impact of the word of mouth information and advertising on the brand perception that in turn will also moderate the customer's purchase decision.

For Brand Association, the highest value is recorded for Apple (14.180) and the lowest for Blackberry (10.700). For Brand Association, the same three brands are close together: Apple, Samsung, and Sony (with values above 14.000) and with equal similar standard deviation values, except for Apple, which has a significant lesser standard deviation value. Next, come the rest of the brands (with values between 10.700 and 12.900), except for Blackberry, which is alone in the last place (with 10.700). It is important to note here that the strength of Apple's brand associations is based on the relationship of smartphones with other devices with technological implications (iPods, iPads, iMacs) and, therefore, it is stronger than the ones that can be created by Samsung, for example. Keller ([42], p. 7) stated that "the favorability and strength of brand associations can be affected by other brand associations in memory." It is pretty much evident that Apple has a very straightforward communication message that might strengthen the associations with its brand. It is also important to note that Wollenberg and Thuong [82] found that the price of the handset has an influence over the brand perception. The association of a higher price to the Apple brand could create a positive impact on how the brand is perceived by the customers.

And finally, for Brand Loyalty, the highest value is for Apple (21.657) and the lowest is for LG (14.385). Therefore, one can say that the Apple brand appears to have the highest overall perception, which might be supported by the corresponding highest values in the other components (except for Brand Awareness). For Brand Loyalty, two brands are close together: Apple and Samsung (with values above 20.500). It is interesting to note that this component showed the highest standard deviation values in all brands. Next, come Sony, Nextel, and Motorola (with values between 16.800 and 17.100), with Nextel having a higher value than Sony and Motorola in standard deviation. Then, we have a third group (Blackberry, HTC, LG, and Nokia) with values between 14.300 and 15.700. It is important to note that Kantar Worldpanel [39] stated that there are three factors influencing Apple buyers' inclination to skip the pre-purchase research process: loyalty through experience, advocacy, and brand strength. Also, in another study, Kantar Worldpanel [38] stated that despite Android's leadership in 2013, Apple reigns in important areas such as loyalty, money spent, the number of heavy users, and user recommendation.

In conclusion, we can state that Apple's CBBE values are the highest in almost every component; it is, nevertheless, important to notice that its values are very similar to those of Samsung. Important to also note is that although Blackberry has the lowest values on all other CBBE components, it does not come last in the overall brand perception. Last in the overall brand perception is Nokia, followed by LG. The results for Blackberry show a downward trend that puts that brand in serious trouble in the medium term. It is interesting to see, however, that Blackberry does have the highest standard deviation in the overall brand perception (7.219),

which means high perceptual differences among interviewees. LG, with the lowest standard deviation (3.871), shows more consistency in the interviewees' responses.

Furthermore, the very sharp increase in the handsets imports from China to Peru may indicate that the local market might be very sensitive to price and, therefore, although the brand equity is higher for Apple than for any other brand, customers might end up buying a cheaper alternative, among which Samsung is one.

4.2. Second-stage empirical findings

Table 5 provides a summary of the CBBE stochastic efficiency. The table is organized as follows: the columns under each of the four aspiration levels (β), namely 0.900, 0.950, 0.990, and 1.000, represent the probability of a DMU being efficient at the given aspiration level. Strong efficiency (SE) and weak efficiency (WE) are to be interpreted with respect to the aspiration level of 100%. For example, for a sufficiently large number of runs, the Apple brand is found to be efficient 77.5% of the times, out of which 97.7% of the times Apple is strongly efficient, while 2.3% of the times, it is weakly efficient. A similar interpretation applies to the rest of the brands. Furthermore, it can be observed that, at 100% aspiration level, out of the times they are found to be efficient, the brands are strongly efficient at least 90.8% of the times.

TABLE 5. Summary of CBBE stochastic efficiency.

DMU	Name of the brand	Aspiration level (β)				SE	WE	Average stochastic efficiency	Rank	SD	CV
		0.900	0.950	0.990	1.000						
1	Apple	0.950	0.871	0.794	0.775	0.977	0.023	0.984	2	0.039	0.039
2	Blackberry	0.610	0.544	0.483	0.467	0.908	0.092	0.895	9	0.143	0.160
3	HTC	0.733	0.643	0.562	0.543	0.937	0.063	0.934	6	0.125	0.134
4	LG	0.638	0.520	0.418	0.403	0.943	0.057	0.912	8	0.147	0.161
5	Motorola	0.778	0.671	0.581	0.551	0.944	0.056	0.952	5	0.151	0.158
6	Nextel	0.806	0.748	0.690	0.670	0.936	0.064	0.958	4	0.183	0.191
7	Nokia	0.687	0.586	0.508	0.489	0.918	0.082	0.930	7	0.219	0.236
8	Samsung	0.930	0.882	0.819	0.800	0.974	0.026	0.990	1	0.227	0.229
9	Sony	0.893	0.776	0.667	0.630	0.959	0.041	0.979	3	0.260	0.265

Note: SE = strong efficiency, WE = weak efficiency, SD = standard deviation, CV = coefficient of variation.

At first sight, the results depict one interesting phenomenon, which is that at different aspiration levels, the probabilities of the different brands being efficient fluctuate in such a way that they reposition the DMUs relative to the efficiency frontier.

As such, it can be noticed that for an aspiration level of 90%, the brand with the highest probability of being efficient is Apple (DMU 1), followed closely by Samsung (DMU 8). These results are supported by the findings of the Future Labs study (2015), which states that the cell phone top four purchase decision factors are: brand prestige, price, design, and technical characteristics, with more than 44% mentions for each. While the technical characteristics might be the same for the upper tier of cell phone brands and models, in the mind of the customer, the brand prestige and design factors might favor those brands with premium prices (such as Apple, for example), while the price factor might favor those brands linked to price (such as Samsung and others). On the other hand, the brand with the bottommost chances of being efficient is Blackberry (DMU 2), followed

by LG (DMU 4), Nokia (DMU 7), and HTC (DMU 3). It is to be noted that Blackberry was once considered a trademark brand for businessmen in Peru, being very much appreciated in the corporate world mostly due to its capability to manage work emails. However, ever since the launch of the iPhone in 2007, Blackberry has been slow in acknowledging the threat posed by this. Furthermore, the attempt to recover through the launch of the Blackberry Bold and Storm models had been too light to make a difference. This led Blackberry to launch the Priv model with an Android operating system, but this attempt, also, failed to yield the expected outcomes. The latest results show that Blackberry holds 1.8% market share of the cell phone market in Peru [52].

Things differ once the aspiration level changes from 90% to 95%. In this case, Samsung takes over the Apple's position and pushes Apple to the next level. No new entrants are found at the bottommost level; hence, the brands with the lowest chances of being efficient are found within the same cluster of DMUs (LG, Blackberry, Nokia, and HTC), which was found at the aspiration level of 90%; although, we may encounter a slight shift in the relative positions of the DMUs within the cluster, at various levels of aspiration.

Moreover, there is no significant difference registered in the order of the brands between aspiration levels of 95% and 99%. Finally, at the 100% aspiration level, all the brands attain their lowest probabilities of being efficient when compared to the other aspiration levels. However, at the other aspiration levels, the relative positions remain intact among the brands, for instance, the order represented by Samsung, followed by Apple, Nextel, Sony, and Motorola. The results also support the theory that the increase in the aspiration level is associated with the gradual decrease in the chances of the DMUs being efficient.

Furthermore, Table 5 also provides the average stochastic efficiency scores, which vary between 0.895 for Motorola and 0.990 for Samsung. The results reveal that Samsung is the best performing brand, followed by Apple, Sony, Nextel, and Motorola, while, at the other end, the least performing brand is Blackberry, followed by LG, Nokia, and HTC. It is to be noted that although Samsung enjoys its first position according to this study, still Apple enjoys a better relative position with higher consistency (0.039), which ascertains the lower variability in the customer's perception towards Apple.

The Nextel brand poses an interesting analysis. Nextel used to have a very important brand recall, mostly among corporate users, from 1998 – year in which it entered the Peruvian market, until the 2002–2007 period during which the firm lost its brightness. In an effort to turn its results around, the firm acquired Millicom Peru and was given (through auction) wide band in 2006 and 2007. In 2009, it got into 3G. Despite these efforts, in 2013, Nextel Peru was acquired by Entel (a Chilean telecommunication company) and changed its name to Entel Perú, marking the official disappearance of the Nextel brand in Peru [78]. Although Nextel is no longer sold by Entel Perú, there are still some loyal users of the Nextel brand that are fond of the push-to-talk (PPT) feature that has given the brand its competitive advantage in the past. This might explain the 4th position enjoyed by Nextel, according to the present study. These users will most probably continue to perceive the brand with a positive attitude, at least until it dies completely[2].

The analysis is, furthermore, complemented with an examination of the probabilities of a DMU being in the reference set for other DMUs in the sample; in our case, the probabilities of each brand being in the reference set for the rest of the brands in the sample, which are given in Table 6.

As such, it can be observed that Samsung (DMU 8) has the highest probability to be the peer for both Apple (DMU 1) and Blackberry (DMU 2). Futuro Labs [28] shows partial support for this finding. Samsung has a clear advantage in market share (32% overall in Peru) over its immediate competitors, Motorola (with a 17% market share overall) and Apple (with 14% market share overall). Following a similar line of reasoning, Blackberry (DMU 2) has the relatively higher chance to be the peer for HTC (DMU 3); HTC (DMU 3) for LG (DMU 4); LG (DMU 4) for Motorola (DMU 5); Apple (DMU 1) and Samsung (DMU 8) for both Nextel (DMU 6) and Nokia (DMU 7); Nokia (DMU 7) for Samsung (DMU 8); and Samsung (DMU 8) for Sony (DMU 9).

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[2]Besides Peru, there were Nextel operations in Mexico, Chile, Argentina, and Brazil. Their parent company, Sprint Nextel based in the US, has sold all its Latin American operations.

TABLE 6. Probabilities of the DMUs being in the reference set.

DMU	1	2	3	4	5	6	7	8	9
1	0.000	0.198	0.177	0.208	0.219	0.286	0.248	0.179	0.209
2	0.069	0.000	0.334	0.036	0.031	0.040	0.027	0.025	0.028
3	0.079	0.082	0.000	0.317	0.014	0.031	0.020	0.019	0.019
4	0.056	0.055	0.047	0.000	0.350	0.111	0.190	0.128	0.155
5	0.076	0.089	0.070	0.091	0.000	0.000	0.008	0.006	0.007
6	0.154	0.151	0.113	0.139	0.148	0.000	0.174	0.000	0.000
7	0.174	0.076	0.138	0.046	0.067	0.096	0.000	0.553	0.047
8	0.258	0.223	0.029	0.029	0.035	0.249	0.198	0.000	0.535
9	0.135	0.126	0.092	0.133	0.135	0.186	0.136	0.091	0.000

5. CONCLUSION

The increasing interest in measuring brand equity has led, in time, to the development of many models and techniques, each with different assumptions and approaches. Nevertheless, the existing methods are all absolute measures, concentrated towards the measure of central tendency. By means of employing the DEA technique, this shortcoming is tackled, as this non-parametric approach allows the direct comparison of an entity with its peer or combination of peers to assess its performance; hence, it allows deriving the CBBE as a measure of relative efficiency. The management can, furthermore, derive strategies to improve the inefficient brands, pushing them towards the frontier where the efficient brands enjoy their premium by means of setting aspiration levels in accordance with the company's strategies. The four aspiration levels provided in the present paper can serve as potential ones that may be adopted by the brands under study.

The present paper proposes a satisficing DEA model to evaluate the CBBE under a stochastic environment, which is free from any theoretical distributional assumptions. Unlike the conventional DEA model, which provides the results with certainty, the proposed model provides the efficiency scores and peer information for each DMU under the probabilistic approach. The model has been applied to nine major cell phone brands available in Peru based on data collected through a survey questionnaire, in line with predefined brand equity dimensions confirmed through factor analysis.

The results reveal the positioning of the individual cell phone brands on the market in terms of the brand equity as perceived by the respondents. Each brand has been analyzed on five dimensions: perceived quality, brand awareness, brand association, brand loyalty, and overall brand perception. It is to be noted that the present study is built upon market-driven data; it is in this context, then, that the results should not be generalized beyond the context of CBBE. Moreover, one should try to conduct periodic surveys to understand the dynamic of the frontier, at different aspiration levels. It is this kind of periodic surveys and analyses that can capture provocative results, which may further stimulate research by others; hence, their importance lies within.

The major limitation of the present study consists in the use of consumer perception data. A new entrant (brand) may, thus, play a vital role in the customer's switching behavior from brand to brand. However, this is inevitable for the cell phone brands when compared to other products, such as luxury vehicles, for which the switching behavior is comparatively low. A future scope of the present study could be to integrate the management's perspective into the study of brand equity and benchmark the brands against the brand equity as perceived by the management.

It has been our endeavor to demonstrate the effectiveness of employing satisficing DEA in measuring the CBBE. The proposed approach can be applied to assess the CBBE of any product/service.

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