Iranian Journal of Management Studies (IJMS) *http://ijms.ut.ac.ir/*
Vol. 11, No. 4, Autumn 2018 *Print ISSN: 2008-7055*
pp. 743-767 *Online ISSN: 2345-3745*
DOI: 10.22059/IJMS.2018.214723.672266

A Data Envelopment Analysis Method for Evaluating Performance of Customer Relationship Management

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(Received: September 19, 2017; Revised: June 10, 2018; Accepted: July 16, 2018)

Abstract
Customer relationship management (CRM) is one of the fastest growing management approaches which can lead to stronger competitive position, resulting in larger market share and profitability. In this study, CRM efficiency among the customers of the Iranian banks is analyzed using a network data envelopment analysis (NDEA) approach. To implement CRM in the NDEA model, input, intermediate and output variables are service quality, customer satisfaction and customer loyalty, respectively. This research is a descriptive survey in which the total customers of different Iranian banks in Isfahan comprise the statistical population. The sample included 420 people that were selected by cluster sampling. After distributing questionnaires, only 245 questionnaires were completed. The model is tested via PLS path modeling and confirmed. To rank banks performance, NDEA model is used. Results show the power of NDEA model in the differentiation of the banks since there are no two banks with the same rank. The efficiency of sub-process is also presented to extract the reason of inefficiency in the total process. Because of the adopted research approach, the research results may lack generalization. Therefore, researchers are encouraged to test the proposed propositions further. The paper includes a model for assessing CRM with NDEA model and helps managers rank their companies in the customers' point of view.

Keywords
Data envelopment analysis, Customer relationship management, Network DEA, Service quality.

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Introduction

Understanding how to manage customer relationships has received considerable attention from organizations in recent years. Since customers give companies economic power, organizations are constantly improving their customer relationships and their communication with costumers. As a result, organizations are concentrating on customer-oriented approach instead of brand-oriented marketing. Customer relationship management (CRM) is a great tool in attracting and retaining customers and has an important impact on the success of organizations (Nguyen, Sherif, & Newby, 2007). Transforming organizations into customer-oriented establishments and expanding revenue and profit at the same time is known as CRM (Ebrahimi, Fathi, & Irani, 2016). CRM is a multiple perspective business paradigm which helps companies to have better relationships with their customers to achieve competitive advantage (Ebrahimi et al., 2016). CRM has been implemented in several organizations since it will lead to customer satisfaction, loyalty and in general to an increase in sale (Feinberg & Kadam, 2002; Kotorov, 2002). CRM is an essential tool for delivering superior customer value and will lead to sustaining competitive advantage for organizations (Jensen, 2001).

To manage, to assess and to improve the effectiveness of the CRM, a measurement system or an evaluation tool is essential (Kim, Suh, & Hwang, 2003). This measurement system or tool helps manages to handle quick changes and to compete with other organization. An effective measurement system should provide a better picture for managers on how their CRM polices and their plans are progressing (Winer, 2001).

Several techniques for evaluating CRM have been proposed by researchers such as Balanced Scorecard (BSC) (Shafia, Mahdavi Mazdeh, Vahedi, & Pournader, 2011), multi-criteria decision making (MCDM) methods (Ebrahimi et al., 2016) and Data envelopment analysis (DEA) (Haridasan & Venkatesh, 2011). All of these methods have their own advantages and disadvantages (Dessler, 2000). Choosing a technique for the evaluation of performance depends on the purpose of evaluating or the status and type of the organization.

One of the effective methods to evaluate the efficiency of different decision-making units (DMUs) is DEA, since DEA is a nonparametric method which accounts for qualitative and quantitative measures and transfers multiple inputs into multiple outputs (Kianfar, Ahadzadeh Namin, Alam Tabriz, Najafi, & Hosseinzadeh Lotfi, 2016). This efficiency estimation technique can be used for solving many problems of management such as ranking of DMUs and evaluating CRM policy (Krasnikov, Jayachandran, & Kumar, 2009). DEA is a powerful model for ranking and evaluating DMUs, but, there is a drawback to this model. DEA model considers DMUs as a black box that get inputs and changes them to the output, while the internal linking activities in the DMUs are neglected (Goto, Otsuka, & Sueyoshi, 2014; Xiaoli, Rui, & Qian, 2014). So, when utilizing DEA for efficiency evaluation, only the initial inputs and final outputs are needed, whereas the data related to the internal activities in each DMU is usually omitted. To deal with this problem, Network DEA (NDEA) model is proposed (Sexton & Lewis, 2003). NDEA calculates the efficiency of DMUs with network structure. NDEA is a more beneficial model, since in real world many cases have network structure (Tavassoli, Farzipoor Saen, & Faramarzi, 2015).

In this paper, a customer-oriented evaluation model by NDEA structure is proposed for evaluating the efficiency of CRM in bank branches. While a variety of studies have defined CRM and its elements, this paper tries to suggest some of the most reputable and important of these factors to come to a network CRM to be used in NDEA method. These factors include service quality, customer loyalty, and customer satisfaction that have been discussed in lots of studies (Amin, 2016; Faizan, Yuan, Kashif, Pradeep Kumar, & Neethiahnanthan Ari, 2016; Jiao, Yang, & Zhu, 2012; Wah Yap, Ramayah, & Nushazelin Wan Shahidan, 2012). All of the studies reviewed here support these hypotheses that service quality has a significant impact on customer satisfaction and customer satisfaction has a significant impact on loyalty. So, a network CRM model by two stages is molded by these assumptions. This two-stage CRM model is used in NDEA and presents a novel method to evaluate CRM in bank branches. Since it is a network, one is able to rank DMUs uniquely and more effectively. This proposed method considers customers' ideas in ranking DMUs. Therefore, a customer-oriented method is presented. Another advantage of this proposed model is the consideration of qualitative measures in evaluating the effectiveness of CRM activities. These nonfinancial factors – i.e. service quality, customer loyalty and customer satisfaction – are as important as financial ones. NDEA, therefore, is chosen as an appropriate evaluation tool for the CRM effectiveness measurement.

This paper is organized as follows. First, some preliminary assumptions about DEA and NDEA are explained. The context and background information about CRM are presented in the next section. Then, a network CRM structure is presented to be applied in NDEA evaluation. After that, survey methodology including questionnaire, data collection and model testing is presented. Finally, the modeling results of NDEA and the conclusion of the study are presented.

Preliminaries

The DEA model

The first DEA model was proposed by Charnes et al. in 1978 (Charnes, Cooper, & Rhodes, 1978). This linear programming model was innovated 20 years after Farrell's inspiring work for assessing the activities of not-for-profit entities distribution in public programs (Farrell, 1957). In recent years, DEA has attracted the attention of a large number of researchers in different contexts such as health care, education, manufacturing, retailing, banking, etc. (Cooper, Huang, & Li, 2004).

The first DEA model measured the efficiency of DMUs under the assumption of constant returns to scale named CCR model (Charnes et al., 1978):

$$\begin{aligned} & E_k = \max \frac{\sum_{r=1}^{s} u_r Y_{rk}}{\sum_{i=1}^{m} v_i X_{ik}} \\ & \text{s.t. } \frac{\sum_{r=1}^{s} u_r Y_{rj}}{\sum_{i=1}^{m} v_i X_{ij}} \leq 1, \quad j = 1, \ldots, n, \\ & u_r, v_i \geq \varepsilon, \quad r = 1, \ldots, s; \; i = 1, \ldots, m, \end{aligned} \tag{1}$$

In these formulae, X_{ij}, $i = 1, \ldots, m$ and Y_{rj}, $r = 1, \ldots, s$ denote the ith input and rth output of DMU_j , $j = 1, \ldots, n$. ε is a small number and E_k is the relative efficiency of DMU k, where $E_k = 1$ indicates efficiency and $E_k < 1$ for inefficiency.

Now, suppose a complete process with two sub-processes as portrayed in Fig. (1).

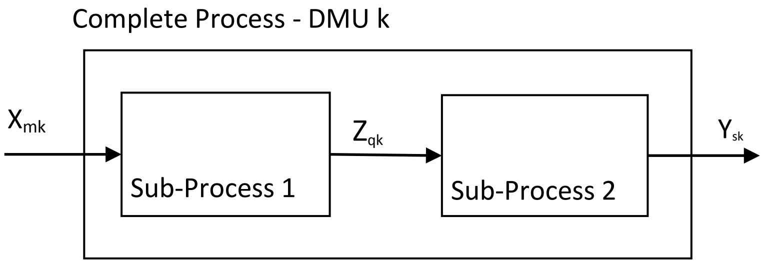

Fig. 1. Two Stage Process

In this fig the complete process uses m inputs $X_{ik},\ i = 1, \ldots, m$ to yield s outputs $Y_{rk},\ r = 1, \ldots, s$ with the intermediate flows of $Z_{pk}, p = 1, \ldots, q$. In other words, the intermediate flows of Z_{pk} are the outputs of stage 1 as well as the inputs of stage 2. Based on this concept, the way to calculate the overall efficiency Ek is shown in Model (2):

$$
\begin{aligned}
& E_k = \max \frac{\sum_{r=1}^{s} u_r Y_{rk}}{\sum_{i=1}^{m} v_i X_{ik}} \\
& \text{s.t.} \ \frac{\sum_{r=1}^{s} u_r Y_{rj}}{\sum_{i=1}^{m} v_i X_{ij}} \le 1, \quad j = 1, \ldots, n, \\
& \frac{\sum_{p=1}^{q} w_p Z_{pj}}{\sum_{i=1}^{m} v_i X_{ij}} \le 1, \quad j = 1, \ldots, n, \\
& \frac{\sum_{r=1}^{s} u_r Y_{rj}}{\sum_{p=1}^{q} w_p Z_{pj}} \le 1, \quad j = 1, \ldots, n, \\
& u_r, v_i, w_p \ge \varepsilon, \quad r = 1, \ldots, s; \ \ i = 1, \ldots, m, \quad p = 1, \ldots, q.
\end{aligned} \tag{2}
$$

Model (2) can be transformed into the following linear program:

$$
\begin{aligned}
& E_k = \max \sum_{r=1}^{s} u_r Y_{rk} \\
& \text{s.t.} \ \sum_{i=1}^{m} v_i X_{ik} = 1, \\
& \sum_{r=1}^{s} u_r Y_{rj} - \sum_{i=1}^{m} v_i X_{ij} \le 0, \quad j = 1, \ldots, n, \\
& \sum_{p=1}^{q} w_p Z_{pj} - \sum_{i=1}^{m} v_i X_{ij} \le 0, \quad j = 1, \ldots, n, \\
& \sum_{r=1}^{s} u_r Y_{rj} - \sum_{p=1}^{q} w_p Z_{pj} \le 0, \quad j = 1, \ldots, n, \\
& u_r, v_i, w_p \ge \varepsilon, \quad r = 1, \ldots, s; \ \ i = 1, \ldots, m, \quad p = 1, \ldots, q.
\end{aligned} \tag{3}
$$

Model (3) is used in this paper to assess the efficiency of bank branches. The proposed CRM model will be introduced in next section.

Proposed model

Proposed CRM Model

A summary of studies on using DEA for CRM evaluation is shown in table below:

Table 1. Summary of CRM Factors Evaluated by DEA

Case Study	CRM Factors	Reference
Swedish pharmacies	customer satisfaction, efficiency and productivity	(Löthgren & Tambour, 1999)
bank branches	internal customer service quality	(Soteriou & Stavrinides, 2000)
bank branches	internal service quality	(Manandhar & Tang, 2002)
-	service quality and customer loyalty	(Haridasan & Venkatesh, 2011)
mobile phone brands	customer satisfaction and loyalty	(Bayraktar, Tatoglu, Turkyilmaz, Delen, & Zaim, 2012)
auto repair services	SERVPERF service quality model	(Lee & Kim, 2014)
bank branches	customer services and satisfaction	(Khalili-Damghani, Taghavi-Fard, & Karbaschi, 2015)
hoteling industry	SERVQUAL service quality model	(Najafi, Saati, & Tavana, 2015)
international airports	service quality perception and profitability	(Merkert & Assaf, 2015)
four star hotels	service quality	(Dabestani, Shahin, & Saljoughian, 2017)

By a quick review of Table (1), it is obvious that none of these researchers have used all essential factors of CRM in their evaluations. Rather, each has used one or two CRM factors for DEA evaluation. Due to the lack of studies on CRM evaluation by DEA and the need to a comprehensive model in CRM efficiency assessment, this research presented a model through the consideration of the important factors of CRM, including service quality, customer satisfaction, and customer loyalty. This model is presented in Fig. (2).

Fig. 2. Proposed CRM Model

In the development of this model, it is assumed that service quality has a direct impact on customer satisfaction and an indirect impact on loyalty. The reason is that several recent studies have revealed that increasing service quality will increase customer satisfaction and satisfied customers are loyal to the company (Faizan et al., 2016; Farhadi, Karimi-Ghartemani, Karimi-Ghartemani, & Raisi-Wastegany, 2012; Horn & Rudolf, 2011; Leenheer & Bijmolt, 2008).

Network CRM model

The CRM parameters by network structure are shown in Fig (2). In the proposed model, service quality influences customer satisfaction, and customer satisfaction impacts loyalty. So, an NDEA method should be implemented since NDEA can handle causal relationship between CRM parameters. In this model customer satisfaction (our intermediate variable) is defined as the output of the first stage and the input of the second stage. Fig (3) presents an overview of the proposed model.

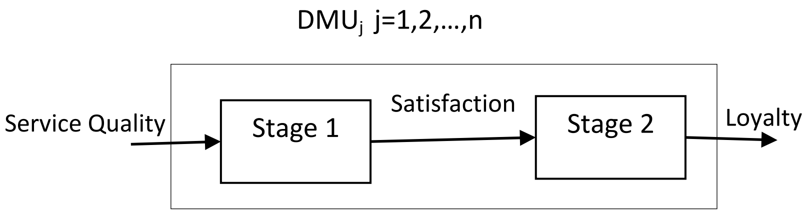

Fig. 3. The Proposed NDEA model

In the proposed DEA model, service quality is considered as the primary input, customer satisfaction is the moderator variable, and loyalty is the output.

Methodology

In this section, the use of NDEA model for evaluating CRM is tested by a case study. In the following sections, the research methodology is presented, which includes survey instrument, the data collection procedure, and the DEA model.

Survey instrument

The data collection in this research is done by a questionnaire. This questionnaire includes items for describing unobservable (latent) variables (service quality, customer satisfaction, customer loyalty). These items are called indicators. This questionnaire is a standard questionnaire, since all indicators were adapted from existing scales. The survey instruments included the Service Quality Scale of the revised SERVPERF, Customer Satisfaction Scale, and the Customer Loyalty Scale of WU K (2011) (WU, 2011). Table (2) shows questionnaire indicators and latent variables.

Table 2. The latent variables and indicators of questionnaire

Latent Variable		Indicator
Service Quality	Tangibles (T)	T1: Convenience of bank's physical facilities (such as decoration).
	Human Factors (HF)	HF1: Accuracy of information shared by staff. HF2: Skills of employees. HF3: Handling customer complaints. HF4: Desirable human relationships with customers.
	Main Services (MS)	MS1: Provide diverse services.
	Systemic Fairness (SF)	SF1: Perform tasks without error. SF2: Paperwork in the banking process. SF3: Sufficient personnel.
	Social Responsibility (SR)	SR1: Bank branch location. SR2: Providing services faster than customer expectations emersion. SR3: The bank's proximity to the parking place.
Satisfaction (S)		S1: Having access to cash. S2: Shorter waiting times for services. S3: Continuous activities. S4: Attracting the customers.
Loyalty (L)		L1: Customer-oriented bank staffs. L2: The maximum honesty of the bank's staffs with customers. L3: Bank account opening or long time bank account maintenance. L4: Recommending the bank to others.

The survey questionnaire was designed using a three-step process. First, the literature of CRM factors (service quality, customer satisfaction, and customer loyalty) was comprehensively reviewed for the indicator variables. As a result this review, the revised SERVPERF model (Cronin & Taylor, 1994) was chosen for the measurement of the indicator variables of service quality. The revised SERVPERF model only measures customer’s experiences and does not ask costumers about their expectations (Cronin & Taylor, 1994). This model is especially appealing for the current study because it is easier to administer, easier to analyze the data, and is more economical. By examining different contexts and different definitions, WU K's (2011) questionnaire was selected to measure customer satisfaction and customer loyalty latent factors.

Secondly, the questionnaire items were prepared and refined through a series of discussions with a number of experts in the field of humanity and bank managers.

Finally, the survey questionnaire was distributed among 30 customers of the selected banks (these banks are shown in Table 6) as the pre-testing of the pilot study. Feedback from this pilot study revealed some questions that were ambiguous and difficult to understand by the bank customers. After omitting these unrelated items, the final questionnaire came to include 20 items (shown in Table 2). All the items were measured on a 7-point Likert scale, with options ranging from 1 as denoting a very negative view to 7 as indicating a very positive view. Reliance on 7-point Likert scales enables customers to make better discriminations. In addition to the model items, the questionnaire included demographic variables (gender, age, marital status and education level).

Sample and Data Collection

The proposed NDEA model is evaluated using data from selected Iranian banks in Isfahan city. One of the basic assumptions of DEA model is the homogeneity of DMUs, which means all DMUs under evaluation, in the same operating environment, peruse the same target with the same processes (Aliheydari Biuki, Khademi Zare, & Hosseyni Nasab, 2016). As the bank’s branches in a specified area are homogeneous DMUs, the cluster sampling was used to select Iranian banks which were located in same region. Cluster sampling is often more economical or more practical than stratified sampling or simple random sampling (Jackson, 2011).

The population of this research was consisted of the customers of Iranian banks in Isfahan city. Clusters were different regions of Isfahan city. Random sampling technique was applied to select one cluster out of these regions. The selected cluster contained diverse banks with different grades (exclusive, grade 1 and grade 2 bank). In this study, just the exclusive and grade 1 bank branches were selected, which resulted in a set of 14 banks branches. These 14 banks have the same conditions, the same region, and approximately the same customers. So, these selected banks were assumed to be homogenous. Fifty percent of these banks were public banks and the others were private.

In the next step, 30 samples were taken from each of the 14 banks. The result of the sampling procedure is shown in Table (3).

According to the Table (3) in the 14 selected banks, 7 banks are private, 7 banks are public, and the total sample size is 420.

Table 3. Sample Size

Bank No.	Banks Name	Type	Sample Size
1	Keshavarzi	Private	30
2	Mellat 1	Private	30
3	Mellat 2	Private	30
4	Melli 1	Government	30
5	Melli 2	Government	30
6	Saderat 1	Private	30
7	Saderat 2	Private	30
8	Saderat 3	Private	30
9	Sepah 1	Government	30
10	Sepah 2	Government	30
11	Sepah 3	Government	30
12	Sepah 4	Government	30
13	Sepah 5	Government	30
14	Tejarat	Private	30
Total Sample Size = 420	**Private**	**50%**	**210**
	Government	**50%**	**210**

Then, in the pilot study, 30 questionnaires were randomly distributed among the customers of these 14 banks to test the normality of the statistical population. The normality of the population was determined using Kolmogorov–Smirnov test (Lopes, 2011). The results of this test are shown in Table (4).

Table 4. Normality test for statistical population distribution

Variable	Significance Level (sig)	Kolmogorov–Smirnov (k-s)	Result
Customer Satisfaction	0.131	1.167	Normal
Loyalty	0.595	0.796	Normal
Service Quality	0.350	0.932	Normal

It can be seen in Table (4) that the pilot study results are significant at the $P = 0.05$ level and all variables have significance levels higher than 0.05. Thus, the overall result of Table (4) reveals that the statistical population of this research is normal.

Finally, 420 questionnaires were randomly distributed among the customers (30 questionnaires in each bank) and 245 questionnaires were completed and returned, which shows a questionnaire return rate of 63 percent.

Model Fitness Evaluation

In order to conduct the model fitness evaluation, Smart PLS M3 Version 2.0 software (Ringle, Wende, & Will, 2005) was used. PLS can be a suitable technique when the model is complex and does not lead to the estimation problems of inappropriate or non-convergent results (Völckner, Sattler, Hennig-Thurau, & Ringle, 2010). Associated statistics implemented in this software is based on the Structural Equation Modeling (SEM) using a Partial Least Squares (PLS). The algorithm of goodness of fit in PLS is presented in Fig. (4).

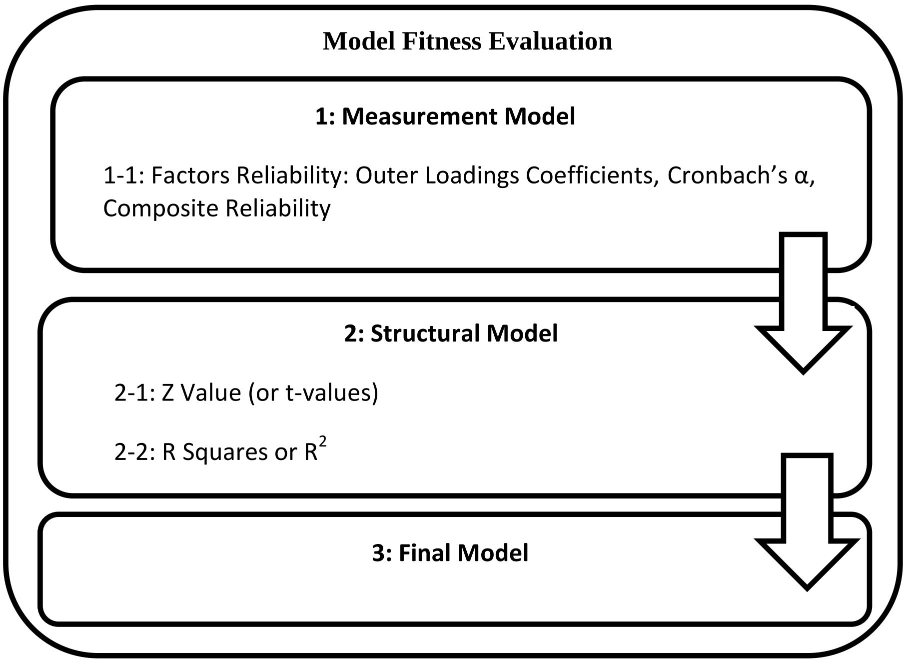

Fig. 4. Fitness Evaluation Algorithm in PLS (Davari & Reza-Zadeh, 2014)

The sections of this algorithm are evaluated in the following lines.

Measurement Model

The first step of measurement model is factors reliability testing, which starts with outer loading. The outer loading (path coefficients) results are presented in Fig. (5).

Fig. (5) shows the item coefficients in the conceptual model. In this fig, the second item of human factor coefficient is -0.089 that is lower than 0.7 and should be omitted. The third item of social responsibility (x53) coefficient is 0.351 and is similarly lower than 0.7, but since by omitting this item there would remain two items for the social responsibility measurement, this item is retained in the model (Fornell & Larcker, 1981). After omitting one of the human factors, the model is run another time and the result is shown in Fig. (6).

The loadings of all questions on their factors are significant ($p < .01$) and greater than 0.7 (except x53) (see Fig. 6 & 7), which ensure the indicator reliability.

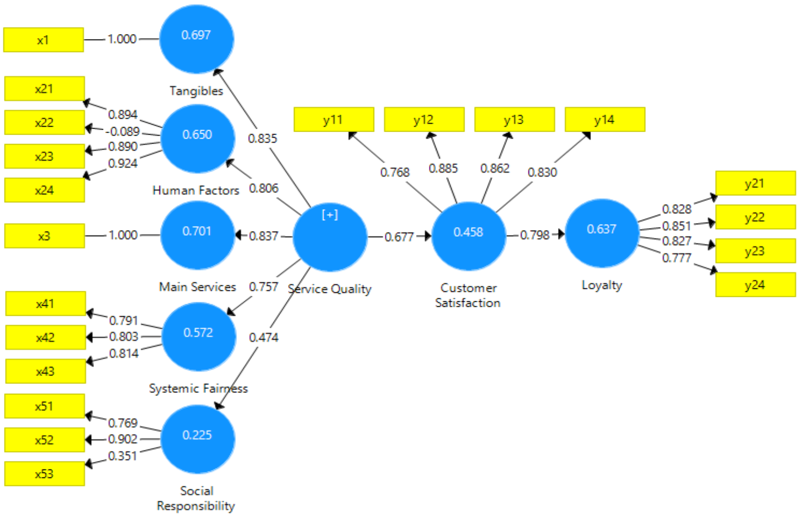

Fig. 5. The Result of Path Coefficients

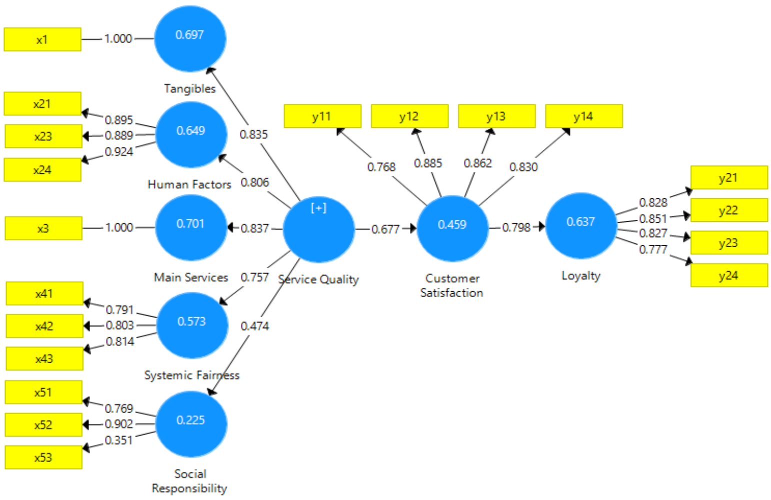

Fig. 6.The Result of Corrected Path Coefficients

The percentages of explained variance (R2 values) for the customer satisfaction and loyalty are .45 and .63, respectively (see numbers on independent variables in Fig. 6).

In this part, Cronbach’s α and Composite Reliability (CR) are tested. The Cronbach’s αs of the model range from 0.72 to 0.85 (see

Table 5). CR values range from 0.84 to 0.90 and Average Variance Extracted (AVE) estimates range from 64% to 70%, which are all in the acceptable range (Bagozzi & Yi, 1988).

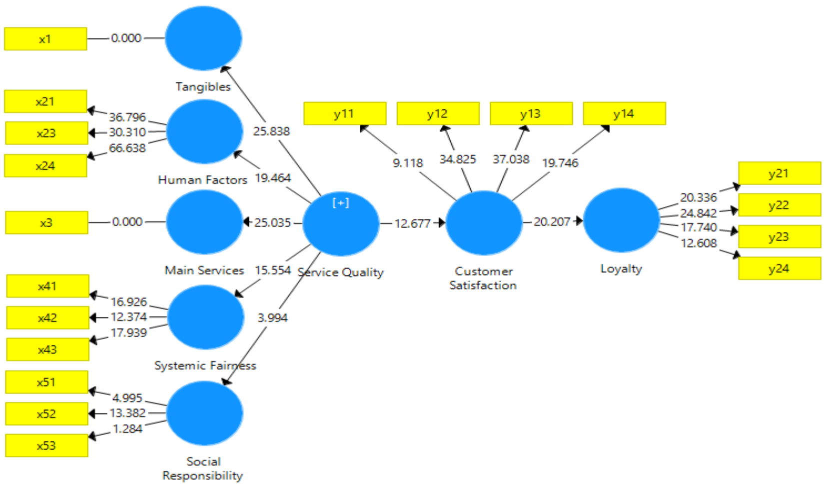

Fig. 7. The Result of t-value

Table 5. Reliability and Validity

Variables	Cronbach's α	CR	(AVE)
Customer Satisfaction	0.857	0.904	0.701
Loyalty	0.839	0.892	0.674
Service Quality	0.725	0.844	0.644
Tangibles (T)	1	1	1
Human Factors (HF)	0.887	0.930	0.815
Main Services (MS)	1	1	1
Systemic Fairness (SF)	0.725	0.844	0.644
Social Responsibility (SR)	0.753	0.735	0.509

In addition, the discriminant validity is tested in the PLS model using the criterion of Fornell and Larcker (1981) (Fornell & Larcker, 1981). According to this test, a latent variable should share more variance with its assigned indicators than with any other latent variable. As it is shown in Table (6), each of the latent variables meets these requirements, in support of the discriminant validity.

Table 6. Discriminant Validity

Variables	Customer Satisfaction	Loyalty	Service Quality
Customer Satisfaction	0.837		
Loyalty	0.798	0.821	
Service Quality	0.517	0.491	0.803

Structural Model

In this section, the model t-values are analyzed. A nonparametric bootstrapping procedure is applied to evaluate the significance of the path coefficients (Davison & Hinkley, 1997; Henseler, Ringle, & Sinkovics, 2009). As the obtained results demonstrate, the impact of service quality on customer satisfaction and the effect of customer satisfaction on loyalty are positive and significant (t value > 1.96 in Fig 5). In the following lines, the R Squares evaluation results are shown in table (7).

Table 7. R2 Values

Variable	Service Quality					Satisfaction	Loyalty
	Tangibles	Human Factors	Main Services	Systemic Fairness	Social Responsibility		
R^2	0.697	0.649	0.701	0.753	0.225	0.459	0.637

The value of R^2 is only calculated for endogenous (dependent) variables, and the value of exogenous variables is zero. R^2 values for endogenous variables are assessed as follows: 0.67 (substantial), 0.33 (moderate), 0.19 (weak) (Davari & Reza-Zadeh, 2014). In this model Social Responsibility is a weak variable, Customer Satisfaction is a moderate variable and the other variables are approximately substantial variables in predicting independent variables.

Then the Q^2 values are calculated (Table 8). In addition to evaluating the scale of the R^2 values, in different models the Stone-Geisser's Q^2 value should also be examined (Geisser, 1974; Stone, 1974). This measure is an indicator of the model's predictive relevance that, correctly forecasts the reflective measurement models of endogenous constructs and endogenous single-item constructs. Davari and Reza-Zadeh (2014) have suggested that values of 0.02, 0.15 and 0.35 have weak, medium and large effects, respectively.

Table 8. Q2Values

Variable	Service Quality					Satisfaction	Loyalty
	Tangibles	Human Factors	Main Services	Systemic Fairness	Social Responsibility		
Q^2	0.667	0.497	0.681	0.340	0.091	0.298	0.401
effect	large	large	large	medium	weak	medium	large

As it is seen in table (8), all variables except one have the medium and large effects and it is a good value for Q^2.

Redundancy is the amount of variance in an endogenous construct explained by its independent latent variables. To produce redundancy, it is necessary to multiply the R^2 value by communality. Communality is the square of a standardized indicator's outer loading (Hair, Hult, Ringle, & Sarstedt, 2014). High redundancy means high ability to predict (Fornell & Larcker, 1981).

$$\text{Redundancy} = \text{Communality} \times R^2 \quad (4)$$

Table 9. Redundancy Values

Variable	Service Quality	Tangibles	Human Factors	Main Service	Systemic Fairness	Social Responsibility	Satisfaction	Loyalty
R^2	0.000	0.697	0.649	0.701	0.753	0.225	0.459	0.637
Communality	0.201	1.000	0.557	1.000	0.292	0.146	0.4787	0.439
redundancy	0.000	0.697	0.361	0.701	0.220	0.033	0.220	0.280
average redundancy	0.314							

The average redundancy reveals that the latent variables predict 31% of the variability of endogenous indicators.

Final Model

Goodness of fit index has been developed as an overall measure of the model fit for PLS-SEM. The values of 0.02, 0.15 and 0.35 present weak, medium and powerful GOF index, respectively. GOF Index calculated by the following formula:

$$GOF = \sqrt{(\overline{communality}) \times (\overline{R\ square})} \quad (5)$$

In this study, the value of GOF is equal to 0.514, which is greater than 0.35 and this means a powerful GOF index.

In this section the presented Network CRM model was confirmed in validity, reliability and path coefficients. So this model is ready to structure the NDEA model for evaluating and ranking different DMUs.

Modeling Results of NDEA

Modeling Inputs

The average values of service quality, customer satisfaction, and loyalty for each bank branch is determined and shown in Table (10).

Table 10. Input Data for NDEA

Banks name	Branch No.	Primary Input	Mediator	Final Output
		Service Quality	Customer Satisfaction	Loyalty
Keshavarzi	1	3.40	3.55	4.05
Melat 1	2	6.20	5.50	5.07
Melat 2	3	5.80	4.85	4.90
Melli 1	4	5.60	5.50	5.07
Melli 2	5	4.23	4.42	4.96
Saderat 1	6	5.10	4.82	4.77
Saderat 2	7	5.11	4.30	5.02
Saderat 3	8	5.71	5.39	5.78
Sepah 1	9	5.90	5.61	5.99
Sepah 2	10	5.70	5.20	5.50
Sepah 3	11	5.60	5.15	5.35
Sepah 4	12	5.80	5.62	5.73
Sepah 5	13	5.12	5.16	5.18
Tejarat	14	4.83	4.00	4.63

As it is seen in Table (10), there are 14 DMUs and for each of these DMUs the primary input, mediator, and final output are calculated.

Analysis and Findings

NDEA model formulation in Model (3) is used to assess the efficiency score of the bank branches. This model was run separately for each bank and the results are shown in Table (11). This table presents the values of v_i, w_p and u_r, E_k^T (total efficiency score obtained from solving the NDEA model) as well as E_k^1 and E_k^2 (the efficiency score of each sub-processes).

Table 11. Sub-Processes and Total Efficiency Scores

DMU$_k$	v_i	w_p	u_r	E_k^T	Rank	E_k^1	Rank	E_k^2	Rank
1	0.294	0.281	0.241	0.976	1	1.000	1	1.000	1
2	0.161	0.154	0.132	0.670	14	0.903	11	0.794	13
3	0.141	0.172	0.165	0.693	13	0.818	12	0.867	11
4	0.146	0.179	0.171	0.742	12	1.000	1	0.794	13
5	0.194	0.236	0.226	0.961	2	1.000	1	0.962	6
6	0.161	0.196	0.188	0.767	11	0.924	8	0.852	12
7	0.160	0.196	0.187	0.805	7	0.805	13	1.000	1
8	0.144	0.175	0.168	0.830	5	0.954	7	0.988	5
9	0.139	0.169	0.162	0.832	4	0.980	6	1.000	1
10	0.144	0.175	0.168	0.791	8	0.908	10	0.952	7
11	0.146	0.179	0.171	0.783	10	0.912	9	0.921	9
12	0.146	0.179	0.171	0.839	3	1.000	1	0.936	8
13	0.160	0.195	0.187	0.829	6	1.000	1	0.875	10
14	0.170	0.207	0.198	0.786	9	0.793	14	1.000	1

In Table (11) the values of v_i, w_p and u_r are the coefficients of X_{ik}, Z_{pj} and Y_{rj}, respectively. These numbers represent the contribution of each variable in total efficiency. For example, first DMU has used 23 percent of its total services quality, 18 percent of its customer satisfaction, and 15 percent of its loyalty, and finally, is allocated 63 percent of total efficiency score (E_k^T) calculated by NDEA model. Using Model (3), the total efficiency scores of DMUs may be lower than 1. Thus, each DMU that has the highest total efficiency score is selected as the best DMU. In this evaluation, the best DMU is DMU number 1, which its efficiency score equals to 0.976. Table 8 numbers are calculated by excel software.

In addition, the network CRM is separated into two sub-processes and efficiency of these two sub-processes are calculated using the input-oriented DEA model. An advantage of this calculation is that the efficiency of the two sub-processes can be used to identify the source that causes the inefficiency of the whole system. For instance, both of the sub-processes of DMU number 1 have the efficiency score equal to 1. Consequently, this DMU gets the first rank in total efficiency score. But, while the first process of DMU number 5 is efficient (equal to 1), its second process efficiency score equals 0.962, which causes the inefficiency of the whole system. A problem with this calculation is that the efficiency of the whole process is calculated independently from the two sub-processes, so E_k^T is not equal to the efficiency of $E_k^1 \times E_k^2$.

An advantage of using NDEA for ranking CRM is that this model presents complete ranking of all DMUs, while in evaluating by traditional DEA models many DMUs are classified as efficient and this leads to the failure in ranking all DMUs. The results show the power of network models in separating DMUs; this has been shown in other studies, too (see Khalili-Damghani et al., 2015; Herbert F. & Sanal K., 2011).

Conclusion

In the past few years and due to various problems such as economic and social troubles as well as the governmental authority over the Iranian banking system, customer relationship and its elements have not been taken into account. As a result, the Iranian banks have suffered from the inadequate application of modern marketing; in other words, the nature of CRM remains unclear in the Iranian banks. The proposed methodology equips managers with a useful tool to measure efficiency of their CRM in the customers' point of view and helps them to propose strategies to improve relationship with their customers to achieve the competitive advantage. Iranian banks can also employ the proposed model to monitor their CRM system at different stages.

The proposed ranking method has least four advantages. First, one can get a full ranking of all DMUs using the proposed approach. Second, the proposed NDEA model can be easily used. Third, by calculating the efficiency of the sub-processes concurrently with that of the whole system, one can understand the source of the inefficiency of the whole system. Finally, DMUs can be compared from a customer point of view using our method. In future research, the proposed method could be developed to rank DMUs with more number of inputs and outputs to understand the effect of the number of DMUs.

References

Aliheydari Biuki, tahere, Khademi Zare, hasan, & Hosseyni Nasab, hasan. (2016). Credit Facilities Management by Developing Data Envelopment Analysis. *Management Researches*, *8*(30), 53–74.

Amin, M. (2016). Internet banking service quality and its implication on e-customer satisfaction and e-customer loyalty. *International Journal of Bank Marketing*, *34*(3), 280–306.

Bagozzi, R. P., & Yi, Y. (1988). On the Evaluation of Structural Equation Models. *Journal of the Academy of Marketing Science*, *16*(1), 74–94.

Bayraktar, E., Tatoglu, E., Turkyilmaz, A., Delen, D., & Zaim, S. (2012). Measuring the efficiency of customer satisfaction and loyalty for mobile phone brands with DEA. *Expert Systems with Applications*, *39*(1), 99–106. https://doi.org/10.1016/J.ESWA.2011.06.041

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

Cooper, W. W., Huang, Z., & Li, S. X. (2004). Chance Constrained Dea. In *Handbook on Data Envelopment Analysis* (pp. 229–264). Boston: Kluwer Academic Publishers. https://doi.org/10.1007/1-4020-7798-X_9

Cronin, J. J., & Taylor, S. A. (1994). SERVPERF versus SERVQUAL: Reconciling Performance-Based and Perceptions-Minus-Expectations Measurement of Service Quality. *Journal of Marketing*, *58*(1), 125.

Dabestani, R., Shahin, A., & Saljoughian, M. (2017). Evaluation and prioritization of service quality dimensions based on gap analysis with analytic network process. *International Journal of Quality & Reliability Management*, *34*(4), 530–548. https://doi.org/10.1108/IJQRM-04-2015-0050

Davari, A., & Reza-Zadeh, A. (2014). *Structural Equation Modeling with Smart Pls Software*. Tehran: Jahad Daneshgahi. (In Persian)

Davison, A. C., & Hinkley, D. V. (1997). *Bootstrap methods and their application*. Cambridge ;;New York NY USA: Cambridge

University Press. Retrieved from http://www.worldcat.org/title/bootstrap-methods-and-their-application/oclc/1002492275

Dessler, G. (2000). *Human resource management (8th ed.)*. New Jersey: Prentice-Hall.

Ebrahimi, E., Fathi, M. R., & Irani, H. R. (2016). A new hybrid method based on fuzzy Shannon's Entropy and fuzzy COPRAS for CRM performance evaluation (Case: Mellat Bank). *Iranian Journal of Management Studies*, *9*(2), 333–358. https://doi.org/10.22059/IJMS.2016.56414

Faizan, A., Yuan, Z., Kashif, H., Pradeep Kumar, N., & Neethiahnanthan Ari, R. (2016). Does higher education service quality effect student satisfaction, image and loyalty? *Quality Assurance in Education*, *24*(1), 70–94. https://doi.org/10.1108/QAE-02-2014-0008

Farhadi, F., Karimi-Ghartemani, S., Karimi-Ghartemani, H., & Raisi-Wastegany, J. (2012). Analyzing the Effects of e-CRM on customers Loyalty: A case study of Parsmodir Khazar Enterprise. *Advanced Research in Economic and Management Sciences (AREMS), 7,* 403–409. Retrieved from http://www.mihantarjomeh.com/wp-content/uploads/2014/10/Analyzing-the-Effects-of-e-CRM-on-customers-Loyalty_uj3q9erb.pdf

Farrell, M. J. (1957). The Measurement of Productive Efficiency. *Journal of the Royal Statistical Society. Series A (General)*, *120*(3), 253.

Feinberg, R., & Kadam, R. (2002). E-CRM Web service attributes as determinants of customer satisfaction with retail Web sites. *International Journal of Service Industry Management*, *13*(5), 432–451.

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, *18*(1), 39. https://doi.org/10.2307/3151312

Geisser, S. (1974). A predictive approach to the random effects model. *Biometrika*, *61*, 101–107.

Goto, M., Otsuka, A., & Sueyoshi, T. (2014). DEA (Data Envelopment Analysis) assessment of operational and environmental efficiencies on Japanese regional industries. *Energy*, *66*, 535–549. https://doi.org/10.1016/J.ENERGY.2013.12.020

Hair, J., Hult, G. T., Ringle, C., & Sarstedt, M. (2014). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM). 2014 Faculty Bookshelf*. Retrieved from https://digitalcommons.kennesaw.edu/facbooks2014/39

Haridasan, V., & Venkatesh, S. (2011). CRM Implementation in Indian Telecom Industry–Evaluating the Effectiveness of Mobile Service Providers Using Data Envelopment Analysis. *International Journal of Business Research and Management* , *2*(3), 110–124.

Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. *Advances in International Marketing*, *20*, 277–319. Retrieved from http://www.emeraldinsight.com/doi/abs/10.1108/S1474-7979(2009)0000020014

Herbert F., L., & Sanal K., M. (2011). A model for efficiency analysis of the customer satisfaction process. *Innovative Marketing*, *7*(1), 33.

Horn, C., & Rudolf, M. (2011). Service quality in the private banking business. *Financ Mark Portf Manag*, *25*(2), 173–195.

Jensen, H. R. (2001). Antecedents and consequences of consumer value assessments: implications for marketing strategy and future research. *Journal of Retailing and Consumer Services*, *8*(6), 299–310.

Jiao, Y., Yang, J., & Zhu, Z. (2012). An Empirical Study of Customer Loyalty to Internet Banking in China. In *2012 IEEE Ninth International Conference on e-Business Engineering* (pp. 39–44). IEEE. https://doi.org/10.1109/ICEBE.2012.16

Khalili-Damghani, K., Taghavi-Fard, M., & Karbaschi, K. (2015). Industrial Engineering & amp; Management Systems. *Industrial Engineering & Management Systems*, *14*(4), 347–371.

Kianfar, K., Ahadzadeh Namin, M., Alam Tabriz, A., Najafi, E., & Hosseinzadeh Lotfi, F. (2016). Presentation of a Novel Integrated DEA-BSC Model with Network Structure in Multi

Objective Programmig. *International Journal of Data Envelopment Analysis*, *4*(2), 697–986.

Kim, J., Suh, E., & Hwang, H. (2003). A model for evaluating the effectiveness of CRM using the balanced scorrecard evaluation model for evaluating the effectiveness of CRM and then illustrate the model through a case study. *Journal of Interactive Marketing*, *17*(2), 5. https://doi.org/10.1002/dir.10051

Kotorov, R. P. (2002). Ubiquitous organization: organizational design for e-CRM. *Business Process Management Journal*, *8*(3), 218–232.

Krasnikov, A., Jayachandran, S., & Kumar, V. (2009). The Impact of Customer Relationship Management Implementation on Cost and Profit Efficiencies: Evidence from the U.S. Commercial Banking Industry. *Journal of Marketing*, *73*(6), 61–76.

Lee, H., & Kim, C. (2014). Benchmarking of service quality with data envelopment analysis. *Expert Systems with Applications*, *41*(8), 3761–3768.

Leenheer, J., & Bijmolt, T. H. A. (2008). Which retailers adopt a loyalty program? An empirical study. *Journal of Retailing and Consumer Services*, *15*(6), 429–442.

Lopes, R. H. C. (2011). Kolmogorov-Smirnov Test. In *International Encyclopedia of Statistical Science* (pp. 718–720). Berlin, Heidelberg: Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-04898-2_326

Löthgren, M., & Tambour, M. (1999). Productivity and customer satisfaction in Swedish pharmacies: A DEA network model. *European Journal of Operational Research*, *115*(3), 449–458.

Manandhar, R., & Tang, J. C. S. (2002). The evaluation of bank branch performance using data envelopment analysis: A framework. *The Journal of High Technology Management Research*, *13*(1), 1–17.

Merkert, R., & Assaf, A. G. (2015). Using DEA models to jointly estimate service quality perception and profitability – Evidence from international airports. *Transportation Research Part A: Policy and Practice*, *75*, 42–50.

Najafi, S., Saati, S., & Tavana, M. (2015). Data envelopment analysis in service quality evaluation: an empirical study. *Journal of Industrial Engineering International*, *11*(3), 319–330.

Nguyen, T. H., Sherif, J. S., & Newby, M. (2007). Strategies for successful CRM implementation. *Information Management & Computer Security*, *15*(2), 102–115.

Ringle, C. M., Wende, S., & Will, A. SmartPLS 2.0 (2005). Retrieved from www.smartpls.de. Accessed on October 1, 2009

Sexton, T. R., & Lewis, H. F. (2003). Two-Stage DEA: An Application to Major League Baseball. *Journal of Productivity Analysis*, *19*(2/3), 227–249.

Shafia, M. A., Mahdavi Mazdeh, M., Vahedi, M., & Pournader, M. (2011). Applying fuzzy balanced scorecard for evaluating the CRM performance. *Industrial Management & Data Systems, 111*(7), 1105–1135.

Soteriou, A. C., & Stavrinides, Y. (2000). An internal customer service quality data envelopment analysis model for bank branches. *International Journal of Bank Marketing*, *18*(5), 246–252.

Stone, M. (1974). Cross-validatory choice and assessment of statistical predictions. *Journal of the Royal Statistical Society*, *36*, 111–147.

Tavassoli, M., Farzipoor Saen, R., & Faramarzi, G. R. (2015). Developing network data envelopment analysis model for supply chain performance measurement in the presence of zero data. *Expert Systems*, *32*(3), 381–391.

Völckner, F., Sattler, H., Hennig-Thurau, T., & Ringle, C. M. (2010). The Role of Parent Brand Quality for Service Brand Extension Success. *Journal of Service Research*, *13*(4), 379–396.

Wah Yap, B., Ramayah, T., & Nushazelin Wan Shahidan, W. (2012). Satisfaction and trust on customer loyalty: a PLS approach. *Business Strategy Series, 13*(4), 154–167.

Winer, R. S. (2001). A Framework for Customer Relationship Management. *California Management Review*, *43*(4), 89–105.

WU, K.-W. (2011). Customer Loyalty Explained by Electronic Recovery Service Quality: Implications of the Customer Relationship Re-Establishment for Consumer Electronics E-Tailers. *Contemporary Management Research*, *7*(1).

Xiaoli, Z., Rui, Y., & Qian, M. (2014). China's total factor energy efficiency of provincial industrial sectors. *Energy*, *65*, 52–61.