# Customer Efficiency as a measure of Customer Lifetime-Value: An alternative approach to CLV based Segmentation

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**Abstract- The key objective of segmentation is identifying and targeting those customers who are relatively profitable to retailers. The limitedly available resources drive the retailers to tailor their resources among identified profitable customers within one or more segments. This is required in current market environment where satisfaction of the right segment of profitable customers is of utmost importance driving their loyalty towards the retailer and the retailer's brand. This research has considered Length of association with customers, apart from variables like Recency, Frequency and Monetary-value in measuring customers' relative-worth based on Customer lifetime- value (CLV).**

**The novel contribution of this article lies in calculating customer efficiency using data envelopment analysis (DEA) as a measure of CLV for segmenting the customer's base. The results for the obtained segments using the above proposed approach turns out to be more reliable when compared with weighted RFM based CLV. The approach is demonstrated on the basis of data collected from a leading apparel retailer in India.**

**This methodology would provide a new and better option to the retailers for measuring CLV of their customers, thus aiding them in conducting more robust segmentation and thereby attaining optimum returns on their investments.**

**Keywords – Segmentation; Customer Lifetime Value (CLV); Efficiency; RFM, LRFM;DEA; AHP**

## 1. Introduction

One of the primary marketing tools is segmentation, as the existence of different customer groups imply the need for distinct marketing mixes (Doyle, 1987) targeted at each group. The basic and the most identifiable problem to segment the market base (Kotler, 1980). The basic criterion for proper segmentation is that the segments be "homogeneous within and heterogeneous between" (Moriarty & Venkatesan, 1978). According to Mariorty and Reibstein (1986), the traditional basis of segmentation in consumer markets extends from demographic to socioeconomic variables, extending to lifestyle, personality, behaviour, attitude, usage of product, and purchase-pattern. During the 1980s, in industrial markets, similar kind of variables have been applied to firms rather than to individuals to serve as segmentation bases. However, in recent years, the variables of segmentation for B2C and B2B are well differentiated. Some of the B2B segmentation variables like firm size and type of industry are differentiated and not applicable for B2C customers (Mariorty&Reibstein, 1986). Lately customer lifetime value (CLV) has become a valuable and practical tool to measure the real value of each of the customer segments (Kumar, Shah & Venkatesan, 2006).

Consequently, it is important to develop some refined strategies for customers, based on their value or relative-worth to the firm (Kim et al., 2006) and target them for relationship management, given the limited resources of the marketer. The transition towards a customer-centric approach to marketing, taking the advantage of increasing availability of customer-transaction data, has led to an interest in estimating and understanding Customer Lifetime Value (Benoit & Poel, 2009). CLV is viewed as the present value of the future-cash flows which is associated with a customer (Kotler, 1974; Pfeifer, Haskins & Conroy, 2005). Knowing the CLV of individual customers enables the decision maker to improve the customer segmentation and marketing resource allocation efforts (Kim & Lee, 2007; Kumar, Shah & Venkatesan, 2006) and this in turn lead to higher retention rates and profits for the firm (Hawkes, 2000).

A key component of success in marketing is accurate identification and retention of the right customers (Blattberg& Deighton, 1991). This is the basis of the modern marketing paradigm in relationship marketing. The value of retained loyal customers is observed by McKenna (1993) as a source of competitive advantage. Managing customer relationships is the essence and crux of any business. A satisfied customer is probably the best form of publicity a company can get. This is valid for business-to-business (B2B) as well as business-to-consumer (B2C) scenarios. It is generally considered more efficient for a business to keep its existing customers satisfied, than to focus on customer acquisition with little regard to customer churn (Stone et al., 2000). This implies that not all customers generate equal profits to the firm and therefore, retailers seek to build up their interest to retain the more profitable customers in the long run and allocate resources to the customers accordingly (Kim & Lee, 2007; Kumar, Lemon & Parasuraman, 2006). Therefore, the underlying issue is the identification of segments having higher CLV or relative worth to the retailers than others (Dahana et al., 2019).

There are myriad reasons for increased investigations on the concept of CLV (Gupta et al., 2006) ranging from increasing pressure on marketers to make marketing function accountable, the inefficiency of existing financial metrics and improved information technology techniques making it possible for firms to collect enormous amount of customer information for measuring CLV.

The net worth of a customer to the firm/ organisation is measured by CLV. By calculating the CLV for all the customers, firms can rank the customers on the basis of their contribution to the firm’s profits. Therefore, CLV helps the firm to treat each customer differently based on his or her contribution rather than treating all the customers at par. The importance and relevance of CLV can be understood by the impact it makes on the following two issues:

a) Calculating CLV helps the firm to know how much it can invest its limited resources in retaining the customer so as to achieve a maximum ROI.

b) The CLV framework is also the basis for selecting customers, up-selling product/service to the customers, and deciding on the customer-specific communication strategies

This research paper investigates the role of CLV towards segmentation of customers and identifies a model which segments the customers based on customer’s efficiency as measure for CLV using data envelopment analysis (DEA) and compares the same obtained clusters with the customers’ segments obtained on the basis of CLV obtained through weighted LRFM using analytic hierarchy process (AHP). The results for the obtained segments using the former approach of measuring customers’ efficiency are verified when compared with the later approach of weighted LRFM based CLV. It implies that this new defined model of segmentation using customer efficiency earns its novelty. The term customer efficiency was first introduced by Xue and Harker (2002). It considers all the dimensions of efficiency namely, transactional, value and quality efficiency. Some researches have also indicated a positive linkage between customer efficiency and company's profitability as well as customers' loyalty (Xue et al., 2007). Similar phenomena would logically be exhibited in the retail sector. Therefore, identifying and focussing on customers having high efficiency would pay rich dividends to the retailers. This article has sourced real life data from a leading apparel retailer as a case to evaluate the results from both the approaches and verify the aforementioned premise. Moreover, the proposed methodology would provide an improved option to the retailers for measuring the CLV of their customers and hence aiding them in conducting more robust segmentation exercise. The resulting segments would provide more clarity for targeting segments with high CLV for relationship management, thereby attaining optimum returns on their investments. The research literature in this area was limited till date to calculating efficiency of firms or a strategic business unit (SBUs) to identify and segregate them but this work extends it to calculation of customers' efficiencies for the purpose of segmentation of customer base by identifying the efficiency of each of the customers.

## 2. Theoretical background and Literature review

### 2.1. Customer Relationship Management and Customer Lifetime Value

Relationship marketing gained traction in the 1980s as a potent tool for marketers to take care of existing and reliable customers and build a long-term profitability target (Gomez et al., 2006). The new concept which is born out of the relationship marketing is customer relationship management (CRM).

CRM is based on the premise that successful firms are those that focus on customer retention and relationship development by having customer-centric approach. The underlying philosophy in customer-centric approach is to fulfil clients' needs and provide customized service to them (Safari et al., 2016). On the contrary, product-centric firms are more concerned with portfolio of products (Kumar, 2008).

CRM can be viewed as 'Managerial efforts to manage business interactions with customers by combining business processes and technologies that seek to understand a company's customers' (Kim et al., 2003). Companies are becoming increasingly aware of the many potential benefits provided by CRM such as: (1) Increased customer retention and loyalty, (2) Higher customer profitability, (3) Creation of value to the customer and sense of customized personal attention to the customer, (4) Customization of products and services, (5) Higher quality products and services (Jutla et al., 2001; Stone et al., 1996). When evaluating customer profitability, marketers are often reminded of the 80/20 rule (80% of the profits are produced by top 20% of profitable customers whereas 80% of the costs are produced by top 20% of unprofitable customers) (Duboff, 1992; Gloy et al., 1997).

Though the growth and sustenance of any business depends on customer acquisition and customer retention (Kotler & Cox, 1980), research proves that customer retention is far for profitable than customer acquisition. The core parts of CRM activities are based on understanding customers' contribution to retailer's profitability and retaining more profitable customers for the benefit of the firm (Hawkes, 2000). To cultivate the full profit potentials of customers, many companies already measure and use customer value in their management activities (Gloy et al., 1997; Rosset et al., 2002; Verhoef &Donkers, 2001). The eventual objective of CRM is to attract, maintain and develop long-term relationships with customers.

The concept of customer lifetime value is derived from CRM. According to Peppers et al. (1999), the objective of CRM is to build a closer and deeper relationship with customers and to maximize the lifetime value of a customer to an organization. These days, firms seek to create profitable customers instead of relying more on the sale of goods/services only (Khajvand et al., 2011). Customer value is simply the value that company receives during the period of its relationship with the client (Kumar, Lemon & Parasuraman, 2006). Pfeifer and Farris (2004) have proved that successful companies maintain over 90% customer retention rate. The main tool for CRM, to answer fundamental questions about attracting, retaining, and promoting customers or questions such as: “Which customer is more profitable” and “How to allocate resources among customers” (Gupta et al., 2006) could be customer long-term value (CLV) (Kumar, Lemon & Parasuraman, 2006).

The definition of Customer Lifetime Value has high similarity across several articles. Pearson (2016) defines CLV as the net present value of the stream of contributions to profit that result from customer transactions and contacts with the company or as present value of all future profits generated from a customer (Gupta & Lehmann, 2003; Jain & Singh, 2002). CLV appears under different names, such as Lifetime Value (LTV) (Kim et al., 2006), Customer Equity (CE) and Customer Profitability (Jain & Singh, 2002). Customers across segments differ in the importance they attach to certain values; how they perceive themselves; what stimulates them to recognize needs; and how they interact with society. More importantly, a certain segment may have higher customer lifetime value (CLV) than others (Dahana et al., 2019). Companies identify and evaluate their customers so as to retain their most valuable customers and eliminate the weaker ones to boost their profitability. Therefore, the concept of CLV is derived from CRM (Kumar, Shah & Venkatesan, 2006) or alternatively the objective of CRM is to maximize the CLV and hence profitable customers for the retailer (Khajvand&Tarokh, 2010). This leads us to the core issue of identifying those segments of customers which have higher CLV or relative worth to the retailers as compared to other segment of customers (Dahana et al., 2019).

### 2.2. Customer Lifetime Value Models

CLV prediction can be useful to improve customer segmentation and resource allocation, evaluate competitor firms, customize marketing communication, optimize the timing of product offerings, and determine a firm's market value (Blattberg et al., 2009; Gupta et al., 2004; Kahreh et al., 2014; Kumar et al., 2004; Kumar, Lemon & Parasuraman, 2006). Moreover, a combination of different models, as proposed in aforementioned articles would better capture the underlying customer behaviour (Jasek et al., 2018). Many researchers have suggested various methods to use customer-level data to measure the CLV (Berger & Nasr, 1998; Fader et al., 2005; Rust, Lemon & Zeithaml, 2004; Schmittlein& Peterson, 1994). In measuring CLV, a common approach is to estimate the present value of the net benefit to the firm from the customer over time or NPV (generally measured as the revenues from the customer minus the cost to the firm for maintaining the relationship with the customer) (Blattberg& Deighton, 1996).

The NPV approach (Berger & Nasr, 1998) was extended by Gupta and Lehmann (2003) and reinforced by Pfeifer et al. (2005). CLV prediction of future value allows retailers to effectively allocate marketing spend, identify, and nurture high value customers and mitigate exposure to losses (Pfeifer &Ovchinnikov, 2011). Since the CLV metric is heavily dependent on customer relationships and transaction data, it has mostly been implemented in the relationship-marketing settings (Sunder et al., 2016). Compared with predicting purchase frequency and weekly repeat purchases, forecasts of individual purchases include more customer information and should provide higher accuracy in individual-level forecasts. However, it remains difficult to model individual purchase behaviour, especially with regard to the highly heterogeneous purchase behaviour encountered in categories like grocery and apparel. Finally, to allocate resources optimally, managers cannot simply measure customer lifetime value (CLV), but instead must know how CLV interacts with various elements of marketing mix. Additional research in this direction would address this aforementioned concern (Castéran et al., 2017).

Researchers employed different methods using various models for CLV but each provided different estimates of the expectations of future purchase behaviour. For example, some models consider discrete time intervals and assume that each customer spends a given amount (e.g., an average amount of spending in the data) during an assumed customer lifetime length, to estimate the lifetime value of each customer by a discounted cash-flow method (Berger & Nasr, 1998). In another model, Rust, Lemon, and Zeithaml (2004) combines the frequency of category purchases, average quantity of purchase, brand-switching patterns and the firm’s contribution margin to estimate the lifetime value of each customer. As customer purchase behaviour might change over a customer’s lifetime with the firm, methods that incorporate past customer behaviour to form an expectation of future customer behaviour and, subsequently, the remaining customer lifetime value are likely to have advantages over other methods (e.g., Schmittlein& Peterson, 1994).

One of the ways of segmentation could be based on relative worth of individual customers to the retailers, expressed through Customer Lifetime Value (CLV) (Kumar, 2006). The CLV of individual customer enables the decision maker to improve the customer segmentation and marketing resource allocation efforts (Kim & Lee, 2007; Kumar, Shah & Venkatesan, 2006) and this in turn will lead to higher retention rates and profits for the firm (Hawkes, 2000). Therefore, relative worth of the customers to the retailer can form a potent basis for segmentation exercise and as a corollary contribute to resource allocation, customize marketing communication, optimize the timings of product offerings and estimate a firm's equity (Blattberg et al., 2009; Gupta et al., 2004; Kahreh et al., 2014; Kumar et al., 2004; Kumar, Lemon & Parasuraman, 2006). Despite this concept being customer centric and significant, considering retailers' profitability, it has not been given adequate importance in past segmentation literature. This study proposes to consider the same in the segmentation exercise considering the case of an Indian apparel retailer.

Though Kumar (2005) stated that either these models calculate the lifetime values by only using the past data of customers, or consider the future behaviour but when the current literature on customer lifetime value modelling is examined the models can simply be classified into two groups: the models that consider past customer behaviour and the models consider both past and future behaviours (Hiziroglu&Sengul, 2012). But this classification lacks a comparative analysis within the context of segmentation (Lemon & Tanya, 2006). Every past customer behaviour group model has unique parameters which is directly related to model's characteristics. The future-past customer behaviour models share the same principle for determining the active period of customers and then calculating the net present values of these customers throughout their activation period (Hiziroglu&Sengul, 2012). Based on this principle most of the models use common variable/constant parameters such as retention rate, marketing cost, cash flow ratio and reduction rate.

Some notable studies which are based on various models of future-past customer-behaviour takes different parameters into account to find out the activation period as depicted in the table below (**Table 1**).

**Table 1. List of Observed Parameters in Various Future-Past Customer-Behaviour Models to Derive Activation Period.**

| Parameters in future-pastcustomer-behaviour models | Literature |
|---|---|
| Retention rate | Drèze and Bonfrer (2009); Kumar and Shah (2009); Kumar et al. (2008); Wiesel et al. (2008); Bejou et al. (2006); Bauer et al. (2003); Bruhn (2003); Gupta and Lehmann (2003); Pfeifer and Carraway (2000); Berger and Nasr (1998); Blattberg and Deighton (1996) |
| Service length or tenure (describing the customer's churn probability over time) | Hwang et al. (2004); Rosset et al. (2003) |
| Loyalty | Kim and Cha (2002); McDonald (1996) |
| Purchase Frequency | Ramakrishnan (2006); Chang and Tsay (2004); Fader et al. (2004); Rust, Lemon, and Zeithaml (2004) |
| Recent transaction time (or Recency) | Chang and Tsay (2004); Fader et al. (2004) |

| | |
|---|---|
| Number of purchase period | Dwyer (1997) |

The above-mentioned models of future-past customer behaviour have been cited in various empirical studies. Reinartz and Kumar (2000) and Chen, Yang, and Lin (2009) have utilized model of Berger and Nasr (1998) in retail industry. It was also applied in banking sector (Glady et al., 2009) and petroleum sector (Gloy et al., 1997), telecommunication sector (Hwang et al., 2004) and Gupta et al. (2004) in an internet company. In addition to that, Kim et al. (2006), Guo et al. (2013), Cuadros and Dominguez (2014), Glady et al. (2015) and Wu and Li (2011) used Kim and Kim (1999), Fader et al. (2005), Fader et al. (2004), Kim and Cha (2002) and McDonald (1996) models in their study respectively. Kumar et al. (2008) adapted three different CLV models that belong to Reinartz and Kumar (2000), Venkatesan and Kumar (2004) and Rust et al. (2004) to perform an empirical study in information technology sector.

Recently, customer analytics has invited great deal of attention from both researchers and practitioners. The increased use of data-mining methods and techniques add to development of CLV models in performance analysis on the basis of CLV and evaluation of the optimal method for identifying CLV in various sectors such as retail, banking, insurance, financial services, and telecommunication (Alvandi et al., 2012; Azadnia, et al., 2012; Chen & Fan, 2013; Chen, Kuo, et al., 2009; Cheng & Chen, 2009; Golmah&Mirhashemi, 2012; Hu et al., 2013; Khajvand&Tarokh, 2011; Kim et al., 2006; Lin et al., 2011; Liu & Shih, 2005a; Parvaneh et al., 2012). These aforementioned data-mining techniques include clustering, logistic regression, decision tree, support vector machine, artificial neural network, survival analysis, association rule Apriori algorithm, self-organising maps, and random forests. Though modelling methods and techniques gives the researcher and practitioners the capability of estimating CLV, many companies possess competitive advantages in terms of decision-making based on CLV employing data mining technique. The customer-lifecycle affords a good framework for applying data mining to CRM. Taken on the 'input' side of data mining, the customer lifecycle tells what information is available. Taken on the 'output' side, the customer-lifecycle says what is likely to be interesting (Freeman, 1999).

There are empirical studies in the related literature which has utilized the models of past customer behaviour based on RFM technique or its extensions. These literatures have taken different datasets from various fields like retail (Albadvi&Shahbazi, 2010; Chang & Tsai, 2011; Chen, Kuo, et al., 2009; Hu et al., 2013; Khajvand et al., 2011; Lin & Shih, 2011; Liu & Shih, 2005a Nikkhahan et al., 2011; Shih & Liu, 2008), wholesale (Chuang & Shen, 2008), textile (Golmah&Mirhashemi, 2012), banking (Khajvand&Tarokh, 2011), charity organizations (Jonker et al., 2004) and healthcare (Khajvand et al., 2011). A few researchers have utilised well-known RFM extension called LRFM (or RFML) which include one or more parameters related to relationship length (or period of activity) (Alvandi et al., 2012; Hosseini et al., 2010; Lin et al., 2011; Parvaneh et al., 2012; Wu et al., 2014). RFM models have been widely applied to a wide scope of areas and sectors like marketing industry (Jonker et al., 2006; Spring et al., 1999), on-line industry (Li et al., 2010), travel industry (Ha & Park, 1998; Lumsden et al., 2008), telecommunication industry (Li et al., 2008), government agencies (King, 2007), and financial organizations (Hsieh, 2004; Sohrabi&Khanlari, 2007). Additionally, RFM based models can be used in segmenting customers, calculating customer lifetime value (CLV), observing customer behaviour, estimating the response probability for each offer type and evaluating on-line reviewers (Wei et al., 2010).

### 2.3. Customer Lifetime Value Models using RFM analysis

Considering the past purchase behaviour models for CLV, three models stand out viz. RFM, SOW and PCV (Hiziroglu&Sengul, 2012). Among the above models, RFM has been popularly employed in marketing discipline for almost decades (Gupta et al., 2006). RFM model is most widely used (Gupta et al., 2006), potent (Kumar et al. 2008; Safari et al., 2016), credible (Yoseph& Heikkila, 2018) and popular methodology (Hu & Yeh, 2014). This model considers: Recency of purchase (R), Frequency of purchase (F) and Monetary value of the purchase (M) (Coussement et al., 2014; Goodman, 1992).

As discussed in the previous section, there are various empirical studies namely Fader et al. (2005), Razmi and Ghanbari (2008), Yeh et al. (2009), and Liu and Shih (2005b) that discuss some of the RFM based CLV models and its extensions. Many of them have been implemented in retail domain and illustrated in retail data set. A brief review of RFM-based CLV model by Liu and Shih (2005b) is discussed below.

#### 2.3.1. Model by Liu and Shih (Liu & Shih, 2005b)

These three variables/ factors of RFM model namely R, F and M may have different impacts on various type of industries. Liu and Shih (2005b) has presented these three variables/ factors with variable weights for each of them. A novel methodology was presented in this research to determine relative weights of RFM variables to evaluate customer's lifetime value which is named as W-RFM (Weighted RFM).

To determine the relative weights of RFM variables, analytic hierarchy process (AHP) was used. To judge the weightings of W-RFM experts from the industry were invited.

If $C_I^j$ is integrated rating of cluster $j$, the formulation to find its amount or customer lifetime value is as follows:

$$C_I^j = w_R C_R^j + w_F C_F^j + w_M C_M^j \quad (1)$$

where,
$w_R = weight\ of\ recency, R$
$C_R^j = recency\ rating\ for\ cluster, j$
$w_F = weight\ of\ frequency, F$
$C_F^j = frequency\ rating\ for\ cluster, j$
$w_M = weight\ of\ monetary\ value, M$
$C_M^j = monetary\ value\ rating\ for\ cluster, j$

Earlier, various scoring methods of the above mentioned three variables have been provided by researchers starting from Hughes (2000) assigning similar weights to the different variables followed by Stone (1994) assigning different weights. The variation was based on the prominence assigned to either of the three based on some subjective criteria by different researchers (Hong & Kim, 2012). Hence, Liu and Shih (2005b) applied a more systematic approach using analytic hierarchy process (AHP) for determining relative weights of R, F and M. In some cases where, conventional AHP has its own drawback of incorporating the uncertainty of human judgments (Van Laarhoven&Pedrycz, 1983), fuzzy-AHP can be utilized to nullify the same. Yet, AHP in fuzzy-AHP give the limitation of element dominance and rank reversal in only a few cases.

## 3. Methodology

The proposed methodology of customer segmentation in this work is based on calculation of customer efficiencies of each customer to cluster them into two different segments and validating the efficiency of obtained clusters using calculated CLV of the clusters. The clusters identified based on the comparative analysis between these two methods is a potent measure to validate the effectiveness of the clusters for charting out a focussed marketing strategy.

### 3.1. Weighted LRFM based CLV using Analytical Hierarchy Process (AHP) for Customer Segmentation

This proposed method is an extension of Liu and Shih (2005b) which developed a methodology for segmenting market based on product-specific variables such as the most recent purchased date in a given period, the frequency of purchase in customer's association for the given period and the associated monetary expenses amount from the transactional history of customers to resolve these said issues. These variables in the current work capture the idea of LRFM (Alvandi et al., 2012; Hosseini et al., 2010; Lin et al., 2011; Parvaneh et al., 2012; Wu et al., 2014) by calculating the weight of another variable namely, length (L) or period of activity which is the entire time period for which the customer is associated with the retailer. The fact that the relative importance of these four variables – Recency (R), Frequency (F), Monetary Value (M) and L (Length) can vary depending upon the business scenario allows the use of AHP to find out weighted LRFM (WLRFM). The relative weights along with values of the L, R, F, and M models the CLV in accordance to the extension of Liu and Shih (2005b) as shown in the following model.

If $C_I^j$ is integrated rating of cluster $j$, the formulation to find its amount or customer lifetime value is as follows:

$$C_I^j = w_L C_L^j + w_R C_R^j + w_F C_F^j + w_M C_M^j \tag{2}$$

where,
$w_L = weight\ of\ recency, R$
$C_L^j = recency\ rating\ for\ cluster, j$
$w_R = weight\ of\ recency, R$
$C_R^j = recency\ rating\ for\ cluster, j$
$w_F = weight\ of\ frequency, F$
$C_F^j = frequency\ rating\ for\ cluster, j$
$w_M = weight\ of\ monetary\ value, M$
$C_M^j = monetary\ value\ rating\ for\ cluster, j$

### 3.2. Efficiency measure-based Customer Segmentation using Data Envelopment Analysis (DEA)

The second method takes data envelopment analysis (DEA) as an intelligent instrument to calculate the efficiency of each of the individual customer (Lee & Park, 2005) and segmenting the customers' base into two segments (can be done into more segments depending on the nature of the business). These two segments basically are comparatively more profitable customers and less profitable customers for the company. The more profitable customers are identified here as the highly efficient customers with efficiency more than a certain critical value. This critical value is identified as that tipping point where there is sharp decrease in efficiency when all the efficiencies of the customers are placed in decreasing order. The paper takes output oriented CCR model of DEA to evaluate the efficiencies of the customers considering four output variables namely Recency (R), Frequency (F), Monetary Value (M) and L (Length). The input variable is fixed and taken to be 1, so as to minimize the inputs for a desired level of output to be achieved while maximizing the efficiency. This DEA-CCR model of calculating efficiency of each of the individual customer has been developed from Charnes et al. (1978).

DEA is a data-oriented approach which is in a based on mathematical programming. Based on Farrel's work (Farrel, 1957), DEA was first introduced by A. Charnes, W.W. Cooper and E. Rhodes (Charnes et al., 1978). However, Data Envelopment Analysis is a body of concepts and methodologies that have been incorporated in a collection of models with accompanying interpretive possibilities (Charnes et al., 1997). It is one of the most efficient methods which is primarily used for evaluating the relative efficiency of a set of entities or alternatives popularly known as DMUs (Decision Making Units). DEA is a widely applied non-parametric mathematical programming approach for analyzing the productive efficiency and performance evaluation of decision-making units (DMUs) or firms/alternatives (customers, in this paper) with multiple incomparable inputs and outputs. In recent years, DEA has been applied to a wide spectrum of practical problems (Emrouznejad& Yang, 2018). The objective function value of a linear programming model is basically efficiency.

According to Charnes et al. (1978), the efficiency of any DMU is obtained as the maximum of a ratio of weighted outputs to weighted inputs subject to the condition that the similar ratios for every DMU be less than or equal to unity. One of the most basic DEA models is the CCR model, which was initially proposed by A. Charnes, W.W. Cooper and E. Rhodes. (Charnes et al., 1978).

Cooper et al. (2006) proposed CCR model where for each DMU, the virtual input and output are formed by weights$v_i (i = 1,2,3, \ldots\ldots, m)$ and $u_r (r = 1,2,3, \ldots\ldots, s)$ . It has an assumption of constant return to scale which implies that change in input is proportional to the change in the input. It takes $n$DMUs $(j = 1,2,3, \ldots\ldots, n)$ into consideration, using $m$ inputs $(i = 1,2,3, \ldots\ldots, n)$ to secure $s$ outputs $(r = 1,2,3, \ldots\ldots, s)$. Let $x_{ij}$ and $y_{ij}$ denote the $i^{th}$ input and $r^{th}$ output, respectively, of $j^{th}$ DMU.

$$Virtualinput = v_1x_1, v_2x_2, v_3x_3, \ldots\ldots, v_mx_m$$

$$Virtualoutput = u_1y_1, u_2y_2, u_3y_3, \ldots\ldots, u_sy_s$$

The weights are determined using linear programming so as to maximize the ratio

$$\frac{Virtualoutput}{Virtualinput}$$

The optimal weights mostly vary for each of the DMUs. Thus, the “weights” in DEA are derived from the data instead of being fixed in advance. That results in better weights as compared to AHP. Each DMU is assigned a best set of weights with values that may vary from one DMU to another. The term “best” is used to mean that the resulting weighted output-to weighted input ratio for each unit is maximized relative to all other units when these weights are assigned to the inputs and outputs for every unit. DEA measures the efficiency of each DMU once and hence we need optimization problem to be solved when we have DMUs. These optimization problems then construct a production frontier which is formed only by efficient DMUs. The inefficient DMUs lie below the frontier.

The DEA which was developed by Charnes et al. (1978) takes $n$ DMUs $(j = 1,2, \ldots\ldots, n)$ into consideration, using $m$ inputs$(i = 1,2, \ldots\ldots, m)$to secure $s$ outputs $(r = 1,2, \ldots\ldots, s)$. Let $x_{ij}$ and $y_{rj}$ denote the $i^{th}$ input and $r^{th}$ output, respectively of $j^{th}$ DMU. The efficiency score for any of the DMU, say DMU$_o$, can be evaluated by maximizing the ratio of weighted sum of output to weighted sum of input, subject to the constraints that all data and all weights are positive (or at least non-negative); the resulting ratio must lie between zero and one; same weights for the target unit are applied to all units, consequently, the unit being evaluated cannot choose a better set of weights for its evaluation (relative to other units). Mathematically, it can be expressed as-

$$max.\theta = uy_o \tag{2}$$

subject to

$$vx_o = 1 \quad (3)$$

$$\frac{uy_j}{vx_j} \leq 1\ (for j = 1,2, \ldots, n) \quad (4)$$

$$v \geq 0 \quad (5)$$

$$u \geq 0 \quad (6)$$

where, $u$ and $v$ represents the output weights and input weights respectively and, "$o$" ranges over $1,2, \ldots, n$.

$DMU_o$is CCR-efficient if $\Theta^* = 1$ and there exists at least one optimal $(v^*, u^*)$, with $v^* > 0$ and $u^* > 0$. Otherwise, $DMU_o$ is CCR-inefficient (Cvetkoska, 2011).

## 4. A Business Scenario – Case of a leading Indian Apparel Retailer

The above business scenario takes the example of a leading formal wear apparel retailer in India that deals with stitched and unstitched formal wear materials along with various other formal wear accessories. The data is taken pan India across multiple stores with similar type of inputs to remove any specific store related errors in the data and to align the whole data at the same coherence level.

### 4.1. Data and Variables

This study has been initially based on a data set covering 25938 transactional data points from 6581 unique customers' POS (point of sale data) spread over 23 months. As the CRM can be established, and CLV can be meaningful only if a customer makes a repeat purchase, all the unique customers are filtered for those who have made repeated purchase within the scope of the time period of this study. This resulted in 1908 unique customers having repeated purchase data (length, $L \neq 0$). The final selection of data takes into account 1650 unique customers after filtering and cleaning the data by removing 258 outliers. The variables taken to explain customers' efficiency and customer lifetime value (CLV) in the data are Length (L), Recency (R), Frequency (F) and Monetary value (M) (Alvandi et al., 2012; Hosseini et al., 2010; Lin et al., 2011; Parvaneh et al., 2012; Wu et al., 2014). 'Recency' refers the duration time between last customer purchasing and present time, 'Frequency' refers the total number of customers purchasing during life time and 'Monetary value' refers to the average money spending during past customer purchases (Jonker et al., 2004; Tabaei&Fathian, 2011). Chang and Tsay (2004) added length into original RFM model to extend it as LRFM (Length, Recency, Frequency, and Monetary) model since length measures the time period between the first visit and the last visit of a particular customer. Reinartz and Kumar (2000) stated that RFM model cannot segment which customers have long-term or short-term relationship with the company. With the introduction of length, the relationship between the customer and the company can be determined numerically, thus removing the above lacunae. It is worthy to note that the data set includes a parameter, customers' IDs (masked contact information) to identify repetitive customers of a firm that affects predictive accuracy of the research (Malthouse &Blattberg, 2005).

Length (L), Recency (R), Frequency (F) and Monetary value (M) are the output variables as they provide a measure to anticipate efficient customers by calculating efficiency of each of the customers individually. This data follows few basic assumptions:

(1) All the customers are exposed to nearly similar input variables i.e., similar store environment, store format, in-store service, after sales service, to name a few.
(2) All the customers come with an intention to purchase and have actually made a purchase.
(3) As a corollary to the above, each customer will be equally valuable to the retailer in the initial stage i.e., during initial purchase.

Taking the above assumptions, the input variable is fixed to 1.

After calculating the variables for each of the unique customers from raw POS data, the data in the variables are standardized as done in a general LP (linear programming) approach by dividing data in variable by a common denominator. **Table 2** presents the data variables selected for this study along with their descriptive statistical characteristics of the standardized data.

**Table 2. Data variables and their characteristics.**

| **Variables** | **Length (L)** | **Recency (R)** | **Frequency (F)** | **Monetary value (M)** |
|---|---|---|---|---|
| **Variable Type** | **Output (O1)** | **Output (O2)** | **Output (O3)** | **Output (O4)** |
| **Mean** | 0.320878373 | 0.52615193 | 0.207234596 | 0.326928395 |
| **Standard Error** | 0.007946301 | 0.006735343 | 0.009214604 | 0.017340027 |
| **Median** | 0.189041096 | 0.516438356 | 0.103204615 | 0.12121885 |
| **Mode** | 0.002739726 | 0.556164384 | 0.24333333 | 0.11753 |
| **Standard Deviation** | 0.322780285 | 0.273590932 | 0.374298981 | 0.704355223 |
| **Sample Variance** | 0.104187113 | 0.074851998 | 0.140099727 | 0.496116281 |
| **Kurtosis** | 0.357764686 | -0.297473777 | 43.26282144 | 38.15094791 |
| **Skewness** | 1.190880956 | 0.441257975 | 5.714256912 | 5.528247068 |
| **Range** | 1.24109589 | 1.276712329 | 4.677325185 | 7.306507431 |
| **Minimum** | 0.002739726 | 0.01369863 | 0.015531915 | 0.002674569 |
| **Maximum** | 1.243835616 | 1.290410959 | 4.6928571 | 7.309182 |
| **Sum** | 529.449315 | 868.1506849 | 341.9370842 | 539.4318518 |
| **Count** | 1650 | 1650 | 1650 | 1650 |
| **Maximum** | 1.243835616 | 1.290410959 | 4.6928571 | 7.309182 |
| **Minimum** | 0.002739726 | 0.01369863 | 0.015531915 | 0.002674569 |
| **Confidence Level (95.0%)** | 0.015585904 | 0.013210727 | 0.018073558 | 0.034010792 |

The overall regression accuracy is determined by $R^2$ (coefficient of determination) and adjusted $R^2$ for the data containing 1650 data points. The correlation coefficient is observed to be 0.96 which is closer to 1 which suggests a linear relationship. Since, the count of independent variable is taken more than one in this case, adjusted $R^2$ (0.919171) is a better measure than $R^2$ (0.919367) in terms of accuracy (Black, 2019). Considering the aforementioned value of adjusted $R^2$, it is observed that approximately 92 % variance in the efficiencies (dependent variable) is explained by the independent variables (L, R, F and M). Adjusted $R^2$ adjusts for the number of terms in the model and it increases with the number of independent variables whenever the predictive power of the model increases positively. Considering a 95% confidence interval for the said data, the p-value for the F-statistics is so small signifying that there is evidence that at least one of the independent variables has a linear relationship with the calculated efficiencies. Considering the t-statistics, the p-values for all the independent variables (L, R, F and M) have significant relationship with the dependent variable (calculated efficiencies of the customer) to be considered for the study.

### 4.2. Analysis and Results

Initially the values for L, R, F, and M are calculated for the 1650 unique customers. The same are depicted in **Table3.** L, R, F, and M Values for 1650 Customers - **available in the Mendeley dataset** (*http://dx.doi.org/10.17632/48ngxh788s.3#file-6ac8efa7-8a6a-4028-a30f-076d254edeb9*) After L, R, F, and M values for each of the unique customers are obtained, the efficiencies for each of the customers are calculated as a measure for CLV.

#### 4.2.1. Clustering/ Segmentation based on customers' efficiency using DEA

The efficiency of every customer is calculated based on these afore-mentioned variables using BCC model of DEA (data envelopment analysis) as described in 'Methodology section' (Charnes et al., 1978) and as shown in Table 4. Efficiency Calculation using DEA - available in the Mendeley dataset (*http://dx.doi.org/10.17632/48ngxh788s.3#file-ab10c215-8d5b-478e-b1e9-6d7ec7aa4a35*)

The assumptions for the same are mentioned in 'Data and Variables section'. The customer efficiencies are then arranged in decreasing order to identify the critical efficiency data point where there is sharp decrease in the efficiency. This point will mark the separation of customers into two clusters – the one above the critical point is the more efficient cluster (Cluster 1) and the one below being comparatively the less efficient cluster (Cluster 2). Hence, this critical point divides the data points of customers' efficiencies into top 40 percentile referring to Cluster 1 and rest of the data points to Cluster 2.

The Cluster 1 (top 40 percentile) has 660 number of more efficient customers with an average efficiency of 0.758424 that the retailer needs to focus on in order to obtain maximum profit while minimizing the retailer's input. These customers are designated as highly efficient customers because losing these customers and repeating new acquisition will result in greater cost to the retailer. These customers having comparatively higher efficiencies play a pivotal role in building up the overall lifetime worth of the customers as depicted in **Table 5.** Efficiency Calculation for top 40 percentile customers in Cluster 1 - **available in the Mendeley dataset** (*http://dx.doi.org/10.17632/48ngxh788s.3#file-f4963272-fa99-46d5-bf60-08d84bb1652c*)

The Cluster 2 (rest of the customers) comprise 990 customers which are less efficient than the top 40 percentile customers with an average efficiency of 0.395552. The customers in cluster 2 are less engaged in building the lifetime worth for the retailer as compared to Cluster 1 as shown in **Table 6.** Efficiency Calculation for rest of the customers in Cluster 2 - **available in the Mendeley dataset** (*http://dx.doi.org/10.17632/48ngxh788s.3#file-bd898d28-6890-40a3-be40-f28255921826*)

#### 4.2.2. CLV calculation for each of the clusters based on weighted LRFM using AHP

The CLV for every customer in both the clusters – Cluster 1 and Cluster 2 are calculated using the extended approach of Liu and Shih (2005b) where the relative weights of all the four variables are calculated. This business scenario demands variable relative weights. The relative weights of the L, R, F, and M in accordance to the extension of Liu and Shih (2005b) are as shown below (Table 7).

**Table 7. Weights of L, R, F, and M.**

| L | R | F | M |
|---|---|---|---|
| 0.152653401 | 0.232611525 | 0.32048563 | 0.294249444 |

To determine the relative weights of LRFM variables, analytic hierarchy process (AHP) was used. The calculation for the same is depicted as in **Table 8.** Calculation of Weights of L, R, F, and M using AHP - **available in the Mendeley dataset** (*http://dx.doi.org/10.17632/48ngxh788s.3#file-b89ceb74-aea7-492d-8558-28f11add3a90*)

Based on the values for each of the four variables L, R, F and M, the CLV was calculated for each of the customers in all clusters to obtain the lifetime worth of each of the customers individually. Taking the mean of CLV for both the clusters, it is observed that the CLV of Cluster 1 (top 40 percentile) is more as compared to the Cluster 2 (rest of the customers). The standard deviation for both the cluster is also in the acceptable range.

**Table 9. Average CLV and average efficiency in Cluster 1.**

| | |
|---|---|
| **Avg. CLV** | 0.460486583 |
| **Std. Dev.** | 0.427002052 |
| **Average Efficiency** | 0.758424 |

The CLV calculation for the customers in cluster 1 is depicted in **Table 10.** CLV Calculation for the customers in Cluster 1 - **available in the Mendeley dataset** (*http://dx.doi.org/10.17632/48ngxh788s.3#file-3c3654e0-1650-4c8c-9aa7-fd1f80882a4c*).

**Table 11. Average CLV and average efficiency in Cluster 2.**

| | |
|---|---|
| **Avg. CLV** | 0.249652922 |
| **Std. Dev.** | 0.162722329 |
| **Average Efficiency** | 0.395552 |

The CLV calculation for the customers in cluster 2 is depicted in **Table 12.** CLV Calculation for the customers in Cluster 2 - **available in the Mendeley dataset** (*http://dx.doi.org/10.17632/48ngxh788s.3#file-e8e91b4d-a9e3-468d-9428-b470a986a24c*).

This comparison depicts that average CLV of Cluster 1 is better than that of Cluster 2 which implies that the efficiencies calculated by DEA-CCR model holds true for the data which depicts that customers in Cluster 1 has better and higher efficiencies as compared to Cluster 2.

The high profitability from customers of Cluster 1 indicates that the retail firm should invest significant amount of resources to the customers of Cluster 1, specifically tailored for them. This will help in long-term association of the customers with the firm and the customers will be retained to a greater period of time.

On the other hand, the customers from Cluster 2 having less profitability than customers from Cluster 2 have the potential to be associated with the existing firm the retail firm engages more in identifying the right customers' need.

## 5. Limitation and Further Discussion

The data has been additionally tested for calculating the efficiency of top 30 percentile as well as top 20 percentile, but the adjusted $R^2$ as well as $R^2$ were not found significant enough in these aforementioned two cases as compared to the case for top 40 percentile of the dataset. So, the critical efficiency has been considered only for top 40 percentile of data. It is because different business scenarios result in varied customer data which again may result in different set of profitable segments of customer. It may happen that the data points may give significant adjusted $R^2$ and $R^2$ for some other business scenarios or with industries which means that different business cases would lead to different segments of profitable customers. This limitation of difference in different segments of customers for various business scenario opens a wide gateway of research in varied fields of industries. These segmented customers can be tested and identified for greater worth to the firm on various other controlled and uncontrolled parameters.

Retailers planning to apply this proposed model for an efficient relationship marketing must identify whether this kind of model will do justice to their segmented customers' database. This is because the developed strategies to exploit the segmented clusters may not be based entirely on this model but also incorporate extraneous managerial decisions taken by the firm. For instance, the thought of investing disproportionate amount of specific resources in specific customers' segment or clusters makes undeniable sense when their future behaviour can be predicted perfectly, but makes no sense when future behaviour is unpredictable ($R^2$=0). Consequently, should organizations invest discretionary marketing resources on the identified best and profitable segment of customers or increase the promotional cost for the less efficient and low profitable customers for initiating a robust relationship exercise? These are few research questions that need to be addressed in future research.

### Appendix A. Supplementary data

Supplementary data to this article can be found online from '***Mendeley Data***' at *http://dx.doi.org/10.17632/48ngxh788s.3*

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