MEASURING CUSTOMER LIFETIME VALUE: APPLICATION OF ANALYTIC HIERARCHY PROCESS IN DETERMINING RELATIVE WEIGHTS OF 'LRFM'

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ABSTRACT

The limited availability of resources drives retailers to tailor their resources to identified profitable customers. In the present scenario, when the ROI of marketing is being questioned, the satisfaction of the profitable customers is of utmost importance as it drives their loyalty towards the retailer and the retailer's brand. This research has considered Length of association with customers (L), apart from variables like Recency (R), Frequency (F) and Monetary-value of the purchase (M) in measuring customers' relative-worth based on the calculation of Customer Lifetime-value (CLV). The contribution of this article lies in calculating weights of these variables – L, R, F, and M utilizing AHP and demonstrating the calculation of CLV using weighted LRFM based on data collected from a leading apparel retailer in India. The obtained results for the customer base using the proposed approach is more reliable when compared with traditional non-weighted approaches of RFM based CLV. This methodology will provide a new and better option to retailers for measuring CLV of their customers, thus aiding their decision making about customer-friendly profitable marketing strategies and attaining optimum returns on their investments.

Keywords: Customer Lifetime Value (CLV); AHP; LRFM, RFM

1. Introduction

Neck-to-neck competition among retail firms has led them to think about ways to stay ahead in the market against their respective competitors. This competition is pushing the firms to innovate their methods to identify the right set of profitable customers and fulfill their needs from the limited available resources. This will improve customer satisfaction and retention, and in the long term, will lead to profitability and sustainability. Considering these issues in the Indian market, there is a pressing need to stay ahead in the competitive market. To fulfill the aspirations of Indian consumers towards their respective brands and thereby achieve optimal profitability, the retailers and marketers need to provide the right set of products to the right segment of customers in alignment with proper allocation of resources (Ayoubi, 2016; Jain & Singh, 2002). It is important to understand the value of customers and essential to identify the most profitable customers in order for retailers to retain them (Hawkes, 2000).

Calculation of CLV has many practical applications. Several authors have developed various models for these applications such as performance measurement (Rust et al., 2004), marketing resources allocation (Reinartz et al. 2005; Ma et al., 2008), targeting customers (Haenlein et al., 2006), pricing (Hidalgo et al., 2008), product offering (Shih & Liu, 2008), and customer segmentation (Rosset et al., 2002; Haenlein et al., 2007; Benoit & Van den Poel, 2009).

One of the methods of segmentation could be based on the relative worth of individual customers to the retailers. Relative worth of the customers is expressed through Customer Life Time Value (CLV). RFM has been a popular value employed in the marketing discipline to evaluate lifetime value (LTV) or customer lifetime value (CLV) for decades (Gupta et al., 2006). These three variables/factors of the RFM model namely, R (recency), F (frequency) and M (monetary value) may have different impacts on various types of industries. Liu and Shih (2005) presented these three variables/factors with variable weights for each.

An extended approach by Liu and Shih (2005) captured 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. To calculate the relative weights of L, R, M, and M (i.e., weighted LRFM or w-LRFM), the Analytic Hierarchy Process (AHP) is used to determine the CLV.

The use of LRFM as a modeling tool for measuring loyalty and later for CLV is based on the premise that the variables R, F, and M and later L (length) are critical in deciding the optimal CLV. Interpreting the results of this approach on these aforementioned variables will give a new and novel dimension to sales and marketing strategies by the company for the targeted set of customers by assigning ranks to the customers according to their relative worth to the retail organization.

Constrained resources with retailers demand that they invest judiciously in the most profitable customers. Therefore, identification of those customers is vital for the sustenance of the retailer. Given the plethora of data being captured across the customers' journey and the availability of various analytical tools to identify the customers' segments, identification and development of the most appropriate tool is the first step. Therefore, the question arises whether the present analytical tools are effective enough to carry out the above exercise. If not, then what improvisations are required? This study has identified the gaps in the existing models of LRFM and suggested incorporation of varying weights to all variables, i.e., L, R, F, and M.

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This study has been conducted with customers that have recorded repeat purchase incidence for a specific product category, i.e., apparel in a given economic, business/ store and social environment, with the assumption that any decision to focus the resources on identified profitable customers would be entirely based on the results from this analysis.

2. Literature review

This section familiarizes the reader with two concepts which are also discussed further in this paper in later sections. Particularly, this section focuses on discussing the concept of an extended approach of CLV calculation using a weighted LRFM model and the use of the AHP to calculate the weights of these said variables.

2.1 LRFM for CLV calculation

The value of customers to a firm or organization is determined by customer lifetime value during the life cycle of the customers (Tukel & Dixit, 2013). Customer lifetime value helps firms and organizations allocate limited available resources to their customers by categorizing them and assigning a specific weight to each customer (Greenberg, 2001). A wide variety of marketing strategies can be identified for each customer by suitable calculation of customer lifetime value which can help an organization categorize and classify its customers based on rankings of CLV (Hiziroglu & Sengul, 2012).

The rankings of CLV are evaluated by one of the popular methods namely, the RFM model for emphasis on the customers who are profitable to the firm (Hu & Yeh, 2014). According to Gupta et al. (2006), the RFM model is the most extensively used method and has been applied in the direct marketing area for more than 30 years. The RFM (Recentcy of purchase, Frequency of purchase and Monetary value of purchase) has emerged as a more potent metric to measure the CLV (Safari et al., 2016; Zhang et al., 2015; Kumar et al., 2008). The RFM aids retailers in managing their customers in a profitable manner as resources can be allocated according to various segments of customers based on their relative worth. This ensures their sustainability over a period in the face of uncertain and volatile market conditions. This RFM model takes three major factors into account: a) Recentcy of last purchase (R) which refers to the duration of time between the last customer purchase and the present time, b) Frequency of the purchase (F) which refers to the total number of purchases made by the customer during their life time, and Monetary value of the purchases (M) which refers to the amount of money consumed in a specific period of time (Coussement et al., 2014; Goodman, 1992).

The RFM based CLV method provides a reliable base for measuring lifetime worth of customers and understanding market segmentation with different values of recentcy, frequency and monetary value (Yoseph & Heikkila, 2018). There are numerous scoring methods for these three variables. In the first ever study, Arthur Hughes (who was the founder of the RFM model) considered a method of scoring RFM where customers were separated into five equal groups. According to him, these three variables were given the same weights to calculate a composite score (Hughes, 1994). Whereas, Stone (1994) debated that different businesses have different natures and assigned different variable weights to the RFM measures according to the nature of the business. For example, he proposed the order as F, R, and M to analyze the value offered by customers who have used a credit card since frequency of use matters more in that case of business. More

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recently, a few researchers have claimed that usually recentcy is a major deciding factor since recent customers are comparatively more capable and responsible for growth and development in a given and specified period of the time. Miglautsch (2000) expressed the order of the RFM model as R, F, and M.

Though RFM has emerged as a significant tool for measuring CLV over the years, it is plagued by some gaps. The major objection for these methods of giving scores is that the weight of each variable is determined subjectively and is primarily based on prior knowledge about the business (Hong & Kim, 2012). Therefore, with the purpose of applying a more systematic approach, the Analytic Hierarchy Process (AHP) was used to determine the relative weights of RFM variables to calculate CLV (Liu & Shih, 2005).

Furthermore, the extended approach of Liu and Shih (2005) adds another variable namely, length (L) or period of activity which is the entire time period for which the customer is associated with the retailer, while capturing the idea of weighted-LRFM (Hosseini et al., 2010; Lin et al., 2011; Parvaneh et al., 2012; Wu et al., 2014). Therefore, Chang and Tsay (2004) added this additional variable, 'length' into the original model of RFM, thereby extending it as a LRFM (Length, Recency, Frequency, and Monetary) model where length measures the difference in time period between the first visit and the last visit of a particular customer to a retail store. Also, Reinartz and Kumar (2000) stated that just the RFM model alone cannot segment and explain which of the customers have short-term or long-term relationship with the company or retail firm. With the introduction of length, the relationship between the customer and the company can be determined numerically, thus removing the above gaps. 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 positively (Malthouse & Blattberg, 2005).

2.2 Analytic Hierarchy Process

The Analytical Hierarchy Process (AHP) is a structured technique to organize and analyze complex decisions based on mathematics and psychology. It is a process of using a hierarchy to carry out a wide-ranging evaluation and final selection of one of the alternative solutions for a particular problem. It provides the objective mathematics to process the inescapably subjective and personal preferences of an individual or a group in making a decision. The technique serves as a connecting link between qualitative and quantitative data. It can also be explained in a general manner as a theory of measurement using both qualitative and/or quantitative data. Taliscali and Ercan (2006) demonstrated the "user-friendly" nature and the application of quantitative and qualitative factors in the evaluation of a problem as one of the fundamental advantages of the AHP, in comparison with other MCDM (multi-criteria decision making) methods.

According to Saaty (1990a), the AHP is a technique which is designed to help with the multiple criteria decision making (MCDM) process. The AHP is comprised of three significant components which are: (1) structuring the problem into a hierarchy consisting of objective/goal and subordinate features (decomposition), (2) pair-wise comparisons between elements at each level (evaluation), and (3) propagation of level-specific, local priorities to global priorities (synthesis). The subordinate levels of a hierarchy may consist of objectives, events, scenarios, actions, outcomes, and alternatives.

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Saaty (1990a) developed the mathematical model for this procedure which has two phases. The hierarchical structure of the system is prepared in the first phase. In more common terms, this involves identifying the elements that are involved in the problem and categorizing these elements into a hierarchical tree structure. All the elements which are situated at a higher hierarchical level act on the elements which are located at a level lower. In the second phase, all individual elements are evaluated and the consistency of the evaluated comparison is checked separately. The evaluation works so that all pairs of elements are compared at a given level from the point of view of each element that is located a level higher in the hierarchical structure. The end result of the comparisons is a set of matrices which, after normalization and examination of consistency, serve as the basis for the final evaluation of the problem.

Let n elements $C_1, C_2 \dots C_n$ in the same level of hierarchy be considered for comparison, and let the relative weight (or significance or priority) of C_i with respect to C_j be denoted by a_{ij} and let it be formed into a square matrix $A = (a_{ij})$ of order n with the constraints that $a_{ij} = 1/a_{ji}$, for $i \neq j$, and $a_{ii} = 1$, all i. This kind of matrix is called a reciprocal matrix. If the element C_i is preferred to C_j, then $a_{ij} > 1$. Correspondingly, the reciprocal property, $a_{ji} = 1/a_{ij}$, for $i, j = 1, 2, 3, \dots., n$, always holds true. Here, a_{ij} varies from $1/9$ to 9 based on Satty's fundamental scale of comparison (Saaty, 2008).

Each set of comparisons for a level with n elements requires ${}^{n}C_2 = (n(n-1))/2$ judgements. A positive reciprocal matrix of pair-wise comparisons $A = [a_{ij}] \in R^{n \times n}$ is constructed to accommodate all the comparisons. Then, the priority vector $\omega = (\omega_1, \omega_2, \omega_3, \dots., \omega_n)$ may be derived from this matrix.

All the elements a_{ij} have perfect values when the decision-maker is perfectly consistent in his/her judgements. So, $a_{ij} = \omega_i / \omega_j$. Thus, there is consistency in the weights if they are transitive in nature, that is $a_{ik} = a_{ij} * a_{jk}$ for all i, j, and $k = 1, 2, 3, \dots., n$. Such a matrix is truly ideal and might exist only if the a_{ij} are calculated from exactly measured data. Then, the pair-wise comparison matrix A is said to be consistent and can be represented as $A_c = [\omega_i / \omega_j]$. The consistent priorities are unique and readily available by taking the average of the elements in any column of the comparison matrix A, and then dividing each of them by the sum of all elements of the column.

However, the evaluations of the decision-maker, a_{ij} are not perfect in real practical scenarios. These serve as estimations of the exact ratios ω_i / ω_j only. Such inconsistency in comparison and judgements is more common in practical business scenarios. In that case, matrix A is an inconsistent matrix, which can be taken as a perturbation of the consistent one A_c. Moreover, the inconsistent priorities are not unique and these can be derived using some error estimation technique.

3. Methodology

3.1 Weighted LRFM based CLV using the Analytic Hierarchy Process (AHP)

3.1.1 CLV calculation

The proposed extended approach of Liu and Shih (2005) calculates the weights of the variables of CLV using the AHP while considering 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 and a causal relationship may exist among two or more variables. The relative weights along with calculated values of the variables- L, R, F, and M are used to develop the CLV model in accordance with the extension of Liu and Shih (2005) as shown in the following mathematical model below.

If C_I^j is the integrated rating of cluster j, the mathematical equation to calculate customer lifetime value is as follows:

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

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

3.1.2 Weights calculation using AHP

According to Saaty (1977), a major component of the AHP is the estimation of priorities from pairwise comparison matrices. T.L. Saaty gave the Eigenvector method (EV) in 1998 (Saaty & Hu, 1998). It has been proven by Saaty that the principal eigen-vector of the comparison matrix can be used as a priority vector for consistent and inconsistent preferences (Saaty, 2003).

Most of the alternative methods for obtaining priorities in the AHP are based on some optimization approaches. This means that they consist of an objective function or goal, which measures the distance between an actual solution and an "ideal" solution. Then the problem of priority derivation comes which is to minimize this goal (or objective function) subjected to some additional constraints. One such method of optimization is the Direct Least Squares method (DLS), which tries to minimize the Euclidean distance from the given comparison matrix under additive normalization constraints. Another such method of optimization is the Weighted Least Squares method (WLS), which uses a modified Euclidean norm as an objective function (Chu et al., 1979). The Logarithmic Least Squares method (LLS) makes use of the multiplicative properties of the pairwise comparison matrices and applies a procedure of optimization which minimizes a logarithmic objective function, subject to multiplicative constraints (Crawford & Williams, 1985). This method gives an explicit solution, which is rather simple and convenient from a computational point of view.

Quite a few authors use a goal programming (G.P.) approach for solving the prioritization problem. Byson (1995) describes the logarithmic Goal Programming method (GP), which tends to minimize a linear logarithmic function subject to some linear constraints.

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Currently, the most common and popular techniques for prioritization in the AHP are the EV and LLS. Numerous researchers have attempted to compare these two methods by evaluating their performance to determine which is best. However, their conclusions often remain contradictory. Barzilai (1997), Crawford & Williams (1985), and Zahedi (1986) assert that the LLS outperforms the EV. Other researchers claim that the EV is inferior to the LLS (Saaty, 1990b; Kumar & Ganesh, 1996).

Takeda et al. (1987) applied a greater number of criteria for comparison and tested the major prioritization techniques with a greater number of randomly generated pairwise matrices. Their findings suggest that the LLS is superior to the EV in some of the cases and equal in many other cases.

Golany & Kress (1993) carried out a brilliant comparative analysis among the commonly used methods for deriving priorities. However, they inferred that there is no prioritization method that is superior to the others in any case. All the methods have their own drawbacks and advantages. Moreover, the choice of method for prioritization should only be dictated by the objective of the analysis. This conclusion could defend our study in this area of CLV and our efforts to develop and test using the EV approach for prioritization in the AHP.

When the problem definition demands that the CLV variable should be given a priority weight so that the effective CLV can be calculated, the same can be identified by applying the AHP. This would help the researcher identify the factors that are comparatively influencing more towards the main decision objective. This may allow the researcher to identify the most and least important factors in driving the decision and act accordingly in the required business scenario.

For the same to be effectively realized, the Eigenvector method (EV) of the Analytic Hierarchy Process (AHP) is followed. The first step before the AHP is to standardize the response data taken from the respondents. This must be done to remove the outliers in the data set. The cumulative value for each comparison is taken by taking geometric mean (G.M.) rather than the arithmetic mean (A. M.). The G.M. removes the outliers and hence, $\mathrm{G.M.} \leq \mathrm{A.M.}$

The AHP technique primarily consists of three major operations including hierarchy construction, priority analysis, and consistency verification. Following the steps mentioned in Ho's flowchart (2008), initially, the complex MCDM problems are broken down into their small associated component parts. These criteria are then arranged into multiple hierarchical levels. The hierarchy is comprised of various levels, ranging from the goal (or the objective) to a variety of criteria, sub-criteria, and alternatives situated at the lowest level of the hierarchy. The highest level of the hierarchy has the decision-making objective. The intermediate levels are presented with the criteria that influence the decision. The alternatives occupy the bottom level of the hierarchy (if required by the research question). The first step is to develop the hierarchy tree with the overall goal objective, criteria and alternatives (if required by the research question) which is as follows:

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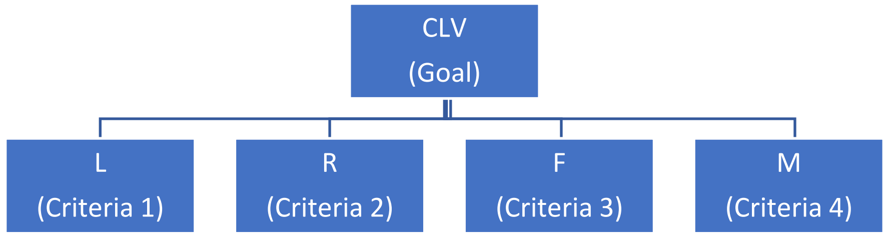

Figure 1 Hierarchy tree of AHP

Next, each cluster is compared in the same level in a pairwise fashion based on the decision maker's own experience and knowledge or by considering the experts' opinion(s). For instance, every two criteria (for one of the examples, recency and frequency) in the second level are compared at each time with respect to the goal/ objective. The comparison matrix, consisting of elements (criteria) in one level in relation to elements at a higher level (goal) is constructed using individual comparisons translated into scale-values. Saaty's fundamental scale is used to quantify the preferences of decision makers (Saaty, 2008).

Some degree of inconsistency may be present in the comparisons since they are carried out through personal or subjective judgments. A final step called a consistency check or verification is done in order to guarantee that the judgments are consistent enough, which is regarded as one of the advantages of the AHP when $n \geq 2$. It is incorporated in order to measure the degree of consistency among the pairwise comparisons by computing the consistency ratio. Here, n is the number of criteria/alternatives. The consistency ratio (C.R.) evaluates the validity of comparisons. Before calculation of the C.R., it is necessary to calculate a consistency index (CI) of an $n \times n$ matrix, which is defined as the ratio $C.I. = (\lambda_{max}\text{-}n)/(n\text{-}1)$. The value λ_{max} is the maximum eigenvalue of the matrix, and n is the matrix dimension. The consistency ratio is calculated as $C.R. = C.I./R.I.$ The R.I. value refers to the random consistency index. If the C.R. value is less than or equal to the specified value, the evaluation within the matrix is acceptable and close to ideal values. However, if it is found that the consistency ratio exceeds the limit (is greater than 10% or 0.1), the decision makers will need to review and revise the pairwise comparisons and therefore improve the evaluation process.

A relatively ranked matrix for each level of the hierarchy is synthesized by the pairwise comparison. The number count of the matrix depends on the number count of elements in each level. The vector of relative weight and maximum eigenvalue (λ_{max}) for each matrix is calculated after all matrices have been created. Once all pairwise comparisons are carried out at every level and are proven to be consistent, the judgments can then be synthesized to determine the priority ranking of every criterion and of its sub-criteria to finally calculate the global weights.

3.1.2.1 Eigenvector Method (EV)

The Eigen vector method is the original Saaty approach to derive the priorities in the AHP (Saaty, 1977). The EV is based on the premise that small perturbations of the

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elements a_{ij} from the perfect ratios ω_i / ω_j will lead to small perturbations of the eigenvalues of the comparison matrix A around the eigenvalues of the consistent one A_c. Saaty proves that the principal eigenvector of A can be used as the desired priority vector using the Frobenius Theorem.

The mathematical derivation of the EV method according to Saaty (1977) is as mentioned. Let a vector ω of order n be found such that $= \lambda\omega$. For such a matrix, ω is said to be an eigenvector (of the order n) and λ is an eigenvalue. For a consistent matrix, $\lambda = n$. For matrices involving human judgment, the condition $a_{ik} = a_{ij} * a_{jk}$ does not hold as human judgments and are inconsistent to a greater or lesser degree. In such a case, the ω vector satisfies the equation $A\omega = \lambda_{max}\omega$ and $\lambda_{max} \geq n$. The difference, if any, between λ_{max} and n is an indication of the inconsistency of the judgments. If $\lambda_{max} = n$, then the judgements are consistent. Finally, a Consistency Index can be calculated from $(\lambda_{max}\text{-}n)/(n\text{-}1)$. That needs to be assessed against completely random judgments and Saaty has calculated large samples of random matrices of increasing order and the consistency indices of those matrices. A true Consistency Ratio is calculated by dividing the Consistency Index (C.I.) for the set of judgments by the index for the corresponding random matrix – random consistency index (R.I.). Saaty suggests that if that ratio exceeds 0.1 the set of judgments may be too inconsistent to be reliable. In practice, CRs of more than 0.1 have to be accepted sometimes. If CR equals 0, then that means that the judgments are perfectly consistent.

Mathematically, the EV method is based on solving the equation:

$$A\omega = \lambda_{max}\omega \text{ and } \lambda_{max} \geq n \quad (2)$$

This approach gives a reasonably good approximation of the priorities vector for small deviations around the perfect evaluations. However, the solutions are not that satisfactory when the inconsistency in the preferences of the decision-maker is large.

$$\sum_{j=1}^{n} a_{ij}\omega_j = \lambda_{max}\omega_i \quad (3)$$

for $j = 1, 2, 3, \dots . n$

Taking the summation over i,

$$\sum_{i=1}^{n}\sum_{j=1}^{n} a_{ij}\omega_j = \lambda_{max}\sum_{i=1}^{n}\omega_i \quad (4)$$

for $i = 1,2,3, \dots . n$ and $j = 1,2,3, \dots . n$

This approach is built on grounds which assume small perturbations of the element a_{ij} from the perfect ratios of ω_i/ω_j. These lead to small perturbations of the eigenvalues of the comparison matrix A. Saaty proved that the principal eigenvector of A can be used as

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the desired priority vector. The EV method is based on solving the equation. It is given by the formula:

$$A\omega = \lambda_{max}\omega, \ \ e^T\omega = 1 \tag{5}$$

The principal eigenvector λ_{max} of A is determined by solving the characteristic equation,

$$|A - \lambda_{max}I| = 0 \tag{6}$$

Then using the value of λ_{max}, the eigenvector $\omega = (\omega_{1,}\ \omega_2, \omega_3\ \ldots .\omega_n)$ is determined from:

$$(A - \lambda_{max}I)\omega = 0 \tag{7}$$

A summary of the methodology behind the AHP involves three basic steps:

Analysis - where the problem is defined and decomposed into a list of related elements and sub-problems (structure the complexity) which helps the decision maker focus on understanding each element according to its importance and effect on the overall process (Islam & Rasad, 2006).

Hierarchy - where a structure is organized into levels of criteria and sub-criteria in relation to a given goal. A matrix of pairwise comparisons at each level is made. The lowest level of different alternatives is compared with respect to each element.

Process- Mathematical methods are used to obtain weights at each level of the hierarchy from the goal to the alternative. A consistency ratio is used to check the consistency of the judgments. To determine the importance of a criterion against another, fundamental scale is applied. This scale quantifies the degree of importance of one element to another such as a criterion against a criterion, or sub-criterion against another sub-criterion (Saaty, 2008).

In a nutshell, the process of developing a model to solve an AHP problem is as follows:

i. Identifying the decision problems,
ii. Listing every evaluation element,
iii. Setting up hierarchical relationship,
iv. Pair-wise comparison,
v. Establishing pair-wise comparison matrix,
vi. Calculating priority weights using any specific (here EV) method,
vii. Performing the consistency check if $n > 2$.

3.2 Research design

This study has been carried out for the apparel retail business in India. The population included all customers purchasing apparel from one specific retailer in India. The data are taken across multiple stores with similar types of input to remove any specific store-related errors in the data and align the whole data at the same coherence level. The sample had 10 identified industry experts to provide ratings through a structured

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questionnaire to the variables for developing the PCM matrix, whereas purchase data from 1650 random customers were analyzed to calculate the CLV. The analysis was conducted on Microsoft Excel using the eigen vector method of AHP (Satty & Hu, 1998).

This study was initially based on a data set covering 25,938 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 purchases within 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 and 685 transaction dates over a span of 23 months after filtering and cleaning the data by removing 258 outliers.

This data follows a few basic assumptions:

(i) 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.
(ii) All the customers come with the intent to purchase and have actually made a purchase.

As a corollary to the above, each customer will be equally valuable to the retailer in the initial stage, i.e., during initial purchase.

4. A business scenario – the case of a leading Indian apparel retailer

The business scenario considered for this study is based on the empirical data collected from a leading apparel retailer that has good brand equity in India. This retailer has a well-established retail chain across India and deals with all types of formal and informal apparel as well as accessories. As the data were collected overall a long period of time, seasonal purchase variations are encompassed in the data set. The national economy was also stable and brand salience was constant during the duration of the study. Therefore, it is assumed that no extraneous variables impacted the results. Apparel as a category exhibits frequent purchase incidence at largely regular intervals with considerable level of customer involvement and customers have the option of repeat purchases from the same retailer or switching to another retailer. Therefore, this category is an appropriate selection for this study.

4.1 Data and variables

After calculating the values of 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 the variables by a common denominator. Table 1 presents the data variables selected for this study along with their descriptive statistical characteristics of the standardized data.

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Table 1
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 and suggests a linear relationship. Since a count of independent variables is done more than once in this case, the 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 the approximately 92 % variance in the efficiencies (dependent variable) is explained by the independent variables (L, R, F and M). The adjusted R^2 adjusts for the number of terms in the model and increases with the number of independent variables whenever the predictive power of the model increases positively. Considering a 95% confidence interval for the data, the p-value for the F-statistics is so small which signifies 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 a significant relationship with the dependent variable (calculated efficiencies of the customer) to be considered for the study.

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5. Analysis and results

The CLV for every customer is calculated using the extended approach of Liu and Shih (2005) where the relative weights of all four variables are calculated. This business scenario demands variable relative weights.

5.1 Problem definition solved by AHP – Eigenvector Method

The Analytic Hierarchy Process (AHP) was used to determine the relative weights of LRFM variables using Microsoft Excel.

Table 2
PCM matrix of AHP

	L	**R**	**R**	**M**
L	1	0.53	0.63	0.48
R	1.88	1	0.66	0.71
F	1.59	1.52	1	1.29
M	2.10	1.40	0.78	1

The relative weights of the L, R, F, and M in accordance with the extension of Liu and Shih (2005) are as shown below in Table 3. The consistency ratio is 0.01492.

Table 3
Weights of L, R, F, and M

L	**R**	**F**	**M**
0.152653401	0.232611525	0.32048563	0.294249444

5.1.1. Sensitivity analysis in AHP

A sensitivity analysis gives insight into how the optimal solution changes when coefficients are changed in the model. To evaluate the sensitivity in the AHP, an free online software, SuperDecisions, was used which was developed Thomas Saaty's team. It is necessary to set an independent variable to see a meaningful sensitivity graph. There is one line for each alternative in the sensitivity window.

The optimum weights w1, w2, w3 and w4 are 0.152653185, 0.232611563, 0.320485744 and 0.294249508 for L, R, F and M, respectively. In this study, frequency (F) which the most significant criteria and has the highest weight comparatively, is set as an independent variable to obtain the sensitivity graph at all nine different data points as shown below. Similarly, sensitivity graph for remaining three criteria can be determined in the same manner.

The change in priority weights for the criteria 'Frequency' can make the weights of the alternatives vary accordingly. To visualize the sensitivity graph, only the top four customers with the best CLV has been taken into consideration as an example.

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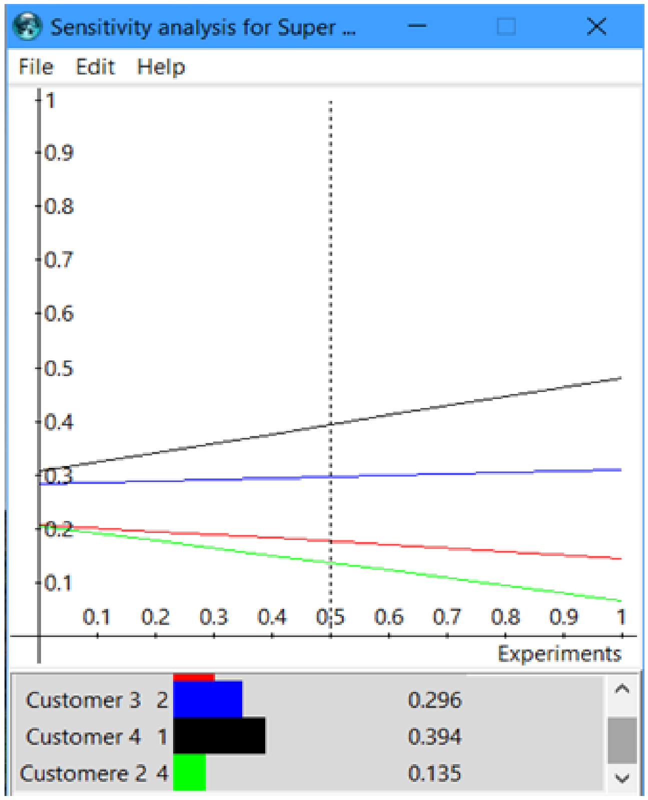

Figure 1 Sensitivity graph of the goal with respect to the criteria "Frequency" for four alternatives

Sensitivity Analysis			**Matrix: Customer selection - Frequency**		
		Change in Weights			
Freqency Paramenter (Actual value)	**Freqency Paramenter (Rounded off value)**	**Customer 1**	**Customer 2**	**Customer 3**	**Customer 4**
0.108	0.1	0.2	0.191	0.285	0.324
0.206	0.2	0.194	0.177	0.288	0.341
0.304	0.3	0.188	0.163	0.29	0.359
0.402	0.4	0.182	0.149	0.293	0.376
0.5	0.5	0.175	0.135	0.296	0.394
0.598	0.6	0.169	0.121	0.299	0.411
0.696	0.7	0.163	0.107	0.301	0.428
0.794	0.8	0.157	0.093	0.304	0.446
0.892	0.9	0.15	0.079	0.307	0.463

Figure 2 Sensitivity analysis of the goal with respect to the criteria "Frequency" for four alternatives at nine different data points

In Figure 1, the priority of the criteria 'Frequency' is plotted on the x-axis and the priorities of the alternatives (all four customers) are plotted on the y-axis. Click on the blue vertical line and drag it to change the priority of activities.

At the point Frequency = 0.5, weight of Customer 4 is 0.394, weight of Customer 3 is 0.296, weight of Customer 2 is 0.135, and weight of Customer 1 is 0.175. Therefore, this graph shows that as the priority of 'Frequency' increases, Customer 4 is always the preferred choice of alternative. However, Customer 2 remains the least preferred alternative out of the four alternatives.

5.2 Calculated CLV results

Based on the values for each of the four variables L, R, F and M, and their respective relative weights, the CLV was calculated for each of the customers to obtain the lifetime worth of each of the customers individually. Taking the mean of CLV for all the customers, the average CLV for all customers is 0.33398639. The standard deviation is also in the acceptable range.

The CLV calculation for all 1650 customers is depicted in Table 4. The CLV calculation for the customers is available in the Mendeley dataset (http://dx.doi.org/10.17632/48ngxh788s.4#file-823d78cc-45e7-4815-b77a-9347e0f34e7c).

A snapshot of the highest and lowest CLV is shown below.

Table 4
CLV calculation for the customers

Customer_ID_Code	**L**	**R**	**F**	**M**	**CLV**
2620	0.939726	0.024658	4.461111	7.023006	3.645425613
3542	0.70411	0.019178	4.692857	5.951064	3.367036304
435	0.405479	0.219178	2.874375	7.309182	3.184799788
1979	1.169863	0.021918	2.28125	7.21954	3.039135377
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
6002	0.027397	0.30137	0.066364	0.027242	0.103569003
811	0.030137	0.276712	0.072277	0.038415	0.103434499
4965	0.043836	0.210959	0.094805	0.031475	0.095408426
4570	0.010959	0.241096	0.082955	0.033099	0.094079657

The higher CLV of a customer expresses higher profitability from these customers. The highest CLV is 3.64542561 with a customer ID code- 2620. The lowest CLV is 0.09407966 with a customer ID code- 4570. This indicates that the retail firm should invest a significant amount of resources specifically tailored for the customers having higher profitability to enhance the customer experience (CX). This will result in long-term retention of customers with the firm.

On the other hand, the customers having a lower CLV have a lower profitability. These customers have the potential of being associated with the existing firm provided the retailers enhance their engagement with these customers to identify their need and render greater service.

6. Suggestions for further discussion

These calculated CLVs of customers can be used in a productive manner to segregate those customers who are more profitable for the firm from those customers who are not profitable for the firm comparatively. Consequently, the customers can be further divided into segments where segments that have similar CLVs are clustered in order to tailor the limited available resources according to the taste, preferences and needs of these customers in each segment as a single entity rather than tailoring the resources for individual customers.

Retailers planning to apply this proposed model for efficient relationship marketing must identify whether this kind of model will do justice to their customer database because the strategies developed to exploit the customers may not be based entirely on this model, but also incorporate extraneous managerial decisions of the firm. For instance, the thought of investing a disproportionate amount of specific resources in specific customers' segment or clusters makes undeniable sense when their future behavior can be perfectly predicted, but makes no sense when future behavior 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 to initiate a robust relationship exercise? A corollary of the above would be to decide what would be the boundary value for customers with high CLV compared to low CLV. These are a 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.4

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