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A CLV-Based Framework to Prioritize Promotion Marketing Strategies: A Case Study of Telecom Industry

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Abstract

Telecommunications is the todays' leading industry. Value Added Services (VAS) is considered as one of the most money making segments of Telecom services. The purpose of this paper is to allocate promotional marketing strategies to customer segments. Therefore, a four-phase practical framework is developed to prioritize marketing strategies based on Customer Lifetime Value (CLV). The first phase focuses on information gathering. Consequently, the CLV of each customer is calculated. Then, the customers are clustered into separated segments based on their CLV scores, using Fuzzy C-Mean. Finally, the appropriate marketing strategy is prioritized for each segment, using Fuzzy TOPSIS technique.

Keywords

Customer Lifetime Value (CLV), customer segmentation, Customer Relationship Management (CRM), fuzzy c-mean, Fuzzy TOPSIS (F-TOPSIS)

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Introduction

Facing with competitive markets in the extremely dynamic economic environment, companies are forced to promote their operations by more efficient and effective planning (Nemati, Madhoshi, & Ghadikolaei, 2017). The first mobile network with international roaming was launched in 1981 in Sweden, Denmark, Finland and Norway. And despite passing less than four decades, the number of mobile users in today's world is going to reach to 5 billion until the end of 2017. Subsequently, Mobile Value Added Services (VAS) is the most commonly used practice in telecom industry, which is affordable for mobile phone users, while has the potential for value creation in many areas for mobile operators (Chen & Hu, 2010). Mobile VAS in short, refers to any services that go beyond the voice service. Despite the variety of VAS types worldwide, the Short Messaging System (SMS) is the most commonly used type of VAS for Iranian subscribers (Kaushik, 2013).

On the other hand, as the marketing paradigm evolves, the importance of long-term relationships with the clients increases. Customer Relationship Management (CRM) is considered as the leading strategy in enterprise environments which are highly competitive (Kim & Kwon, 2003). The main part of CRM activities is to understand the profitability of the customer and maintain customers that are profitable for the company (Gruen & Shah, 2000). To calculate the potentials of overall customer profitability, many companies have tried to estimate the customer value in their operation (Chen, Khoo, & Yan, 2002; Macrae & Uncles, 1997; Rahimi & Kozak, 2017; Wang & Feng, 2012). In this paper, the Customer Lifecycle Value (CLV) is used to calculate customer’s value, as the total benefits of a customer during his/her relationship period (considering past, current and future earnings) (Verhoef & Donkers, 2001). It should be noted that CLV differs from Customer Profitability (CP). CP is defined as the difference between the revenues and the costs associated with the customer relationship during a specified period. (Farris, Bendle, Pfeifer, & Reibstein, 2010; Nemati & Alavidoost, 2018). It can be inferred from the definition that CP measures the past and CLV looks forwards. Hence, CLV can be more useful in shaping managers' decisions. In general, understanding the value of customers and the most profitable customers are essential to retain customers. Therefore, lots of companies are required to evaluate their customers' value and utilize appropriate initiatives to maintain profitable customers.

Until today, the adoption of strategic decisions in the field of marketing was mostly intuitive and empirical, and the lack of an integrated practical framework which jointly brings the scientific models and experts' experience together for the sake of assigning marketing strategies to different customer segments is strongly felt.

Hence, this paper tries to propose a practical framework which calculates CLV for customer segmentation and then allocate marketing strategies to each segment in order to deploy more targeted and personalized marketing strategies. In other words, this study tries to answer the following questions for the strategic planners or marketing managers who are seeking for joint scientific-practical solutions for the strategy implementation:

i. How to estimate the value of the customers in a quantitative way?
ii. How to divide the customer base into few segments with similar purchasing behavior?
iii. And ultimately, how to dedicate the most suited marketing strategy to each customer segment?

Each of the above questions may be fulfilled in previous studies, separately or altogether as Alavidoost, Zarandi, Tarimoradi, and Nemati (2014), Hwang, Jung, and Suh (2004), and Kim, Jung, Suh, and Hwang (2006), but our study is going to propose a comprehensive all-in-one framework to answer the entire above questions, considering the uncertainty of real world data ambiguity by fuzzy logic application. Also, the proposed framework is deployed in a leading telecom company in Iran.

The remainder of this paper proceeds as follows: The second section is devoted to providing a literature review as well as discussion about the latest development of telecommunication services in Iran. Then, the third section develops the research methodology and procedures. Also, the application of techniques and formula is provided, immediately after describing every steps and phases, in order to maintain the linkage between processes and concepts. Finally, the fourth section presents concluding remarks and future direction of the study.

Literature Review

Profitable customer is defined by Kotler (1996) as "a customer that his/her revenues for the company over time is more than the costs that company undertakes for attracting, retaining, and servicing him/her." The CLV has been investigated under various titles, including Customer Value (CV), Customer Life Time Value (CLV), and Life Time Value (LTV). Kumar and Shah (2015) considered the value of a customer life cycle to be net worth, which results from the expected profit of the organization minus the related costs. Libai, Narayandas, and Humby (2002) defined CLVs as the profit which is resulted after all the steps that a company pursues to maintain its relationships with current customers.

According to the literature, CLV definitions would be categorized into three different groups (Abdolvand, Albadvi, & Koosha, 2014). First group of definitions emphasized on "profit" without considering the time value of money. The second group considers "net present value", as the total value of all cash inflows and outflows. The third group defines profit as "present value", meaning the current value of future (and not present) cash flow, discounted to reflect the time value of money.

Until today, significant practical research has been conducted to develop statistical methods for determining how customer value is calculated (Pearce & Hanlon, 2007). Most of researches that estimate the CLV emphasize on the current value that is obtained through customer lifetime transactions, and try to model the CLV through customer retention and customer immigration behaviors. One of the other fundamental methods for calculating the CLV is the RFM method (Berger & Nasr, 1998), which consists of the elements such as exchange novelty, frequency of exchanges, and the volume of the transaction. In another approach, called the *wallet-share method*, calculation of the customer's value is defined as the relative amount of product sold by the organization on the customer's total purchase of the same product in the entire market, along with the given time period (Castéran, Meyer-Waarden, & Reinartz, 2017; Reinartz, Thomas, & Kumar, 2005). One of the other methods proposed in this area is the "customer past value" method (Gupta et al., 2006; Gupta & Lehmann, 2003), which is based on the assumption that the customer's past performance reflects his/her level of profitability in the future, and a scale of past results can be projected as the future value of the customer. Another proposed method for CLV calculation is through applying the interest rate index (Wilson & Hollensen, 2013). In this way, the basis for calculating the CLV is the Return on Investment (ROI) of each customer.

Hwang et al. (2004) developed a novel model for customer life time valuation and customer segmentation based on partial selling positions in wireless communication industry. Kim et al. (2006) proposed a model for analyzing CLV and then segmentation of the customers based on that. After that, strategies were allocated to each customer group, based on their CLV in a wireless telecommunication company. Segarra Moliner and Moliner Tena (2016) presented a predictive model to analyze and assesses customer equity (value, brand, and relationship equity) and their influence on behavior intentions and customer lifetime value (CLV). Amin et al. (2017) proposed an intelligent rule-based decision-making technique, based on Rough Set Theory (RST) to extract important decision rules related to customer churn and non-churn in telecom sector. Coussement, Lessmann, and Verstraeten (2017) developed an optimized model for churn prediction and tested the model with real-world cross-sectional data from a large European telecommunication provider. Sublaban and Aranha (2009) provided insights about how customer equity estimates can help businesses monitor the competition as well as aid managers in making their marketing investment decisions in telecom industry. Ekinci, Ülengin, Uray, and Ülengin (2014) provided a guideline to predict customer lifetime values in banking sector, via Markov decision processes. The proposed framework tried to eliminate the limitations and drawbacks of the majority of previous models.

Due to the simplicity and implementation adoptability to the telecom industry, in this paper, we used the method provided by Razmi and Ghanbari (2009) to determine the CVL; a set of revenues that are obtained after deducting the cost of attracting, selling and serving the customer over the life of its transactions.

According to the literature, to our best knowledge, no study has been made to comprehensively integrate all the different steps through strategic decision making by customer’s value. Hence, the purpose of this research is to develop and implement a comprehensive framework that allocates appropriate marketing strategies to each customer segment in order to help the organization to focus on more valuable customers and retaining them. To achieve this, we need to use a top-notch marketing index such as CLV, which has been used extensively as a global marketing benchmark, in reputable companies such as IBM, Capital One, IGN and etcetera, because of its proven validity and reliability (Gupta, 2009).

Research Methodology

This study has four phases. In the first phase, the required data are collected from a sample of 2000 customers out of 1,600,000 VAS by convenient sampling method. The needed data includes the Mobile Station International Subscriber Directory Number (MSISDN), type of service/services being used by the customer, subscription time, unsubscription time, total cost per month, and total revenue per month. In the second phase, the CLV index of each customer is calculated, according to the data collected in phase one. Noting that three parameters of current value, contractual value and customer loyalty are being considered in calculating the CLV. In the third phase, after calculating the lifetime value, the sample customers will be clustered into different segments, according to their CLV, using Fuzzy C-Mean (FCM) clustering technique. Finally, in the fourth phase, the appropriate marketing promotion strategy, extracted from Kotler 4P marketing mix, is ranked for each customer segment, by using *f*-TOPSIS technique (*Figure 1*). The logic is each customer segment has its specific characteristic and behavior and requires its specific marketing strategy, accordingly.

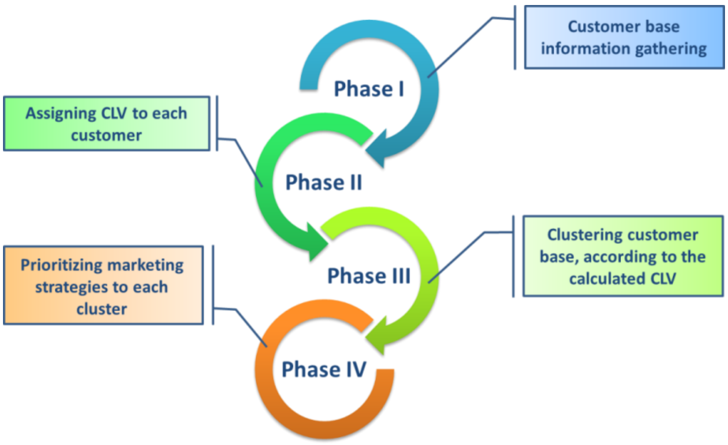

Figure 1. Conceptual framework of the study

Phase 1: Collecting customers' information

At this stage of the study, based on the extracted factors from the review of the life time value background, a randomly selected sample of 2000 customers of SMS-based VAS (including both prepaid and post-pay subscribers) is extracted from the main customers' database of the studied company. It should be noted that because of the novelty of such services, after purifying the customer database, the final number of VAS customers was reduced to 1991.

The customers' database has been gathered from 7 services of women beauty and health tips, sports news, religious horoscope, joke, Hafez horoscope, astrology, and successful management daily tips. The reason of selecting these 7 categories is that in the time of study, only these categories were active in the MCI's SMS VAS system and we used all of them for our case. The customer data required to calculate the CLV index, including cost and income data, were collected in monthly manner, during the seven-month period between January 2016 and July 2016. The final output of the first phase is to calculate the CLV.

Phase 2: Calculating the lifetime value for each customer

As previously mentioned, we used Razmi and Ghanbari (2009) for calculating CLV of the customers. Like many other researchers, they believe that client''s future activities should be considered in calculating the CLV. Future customer benefits can be considered through two dimensions. The first question is will the client contract with the company during the next period? Another important issue is the probability of churn. Perhaps at first glance, these two issues may look closely related, but with a more scrupulous look, they are not. A customer may not continue to contract for the next period and remain loyal to the organization, at the same time. On the other hand, making a contract by a customer for the next period cannot guarantee customer's loyalty to the organization (Rostami, Noroozi, Mokhtari, & nemati, 2016). These two issues should somehow be included in the calculation. In order to quantify them, we have to determine the indicators that are discussed below:

1. Contract index (α): For the possibility of being purchased by a customer in the next period, we can use the last customer purchase time. The most obvious thing is customers typically use different buying patterns over a given period of time. The less time has passed since the last purchase; it is more likely he/she will contract in the next period. The following relation can best display this probability:

$$(1)\ \alpha = T1/\,T2$$

Where:

$0 \leq \alpha \leq 1$: is the probability of customer purchasing in the value estimation period;

$T1$: is the time elapsed between the time of customer attraction and the last purchase; and

$T2$: is the time elapsed between the time of customer attraction and the probability estimation period.

2. Loyalty index (β): if the frequency of purchase by the customers is higher at a given time frame, the customer's loyalty to the organization would be higher and consequently, the likelihood of losing the customer would be less. Therefore, the loyalty coefficient of β, which is a decimal number between 0 and 1, is calculated as follows:

$$(2)\quad \beta = n / N$$

Where:

$0 \leq \beta \leq 1$: is the customer loyalty to organization;

n: is the number of periods the buyer has purchased; and

N: is the number of periods under review.

In order to calculate the CLV, we must first calculate the past profit based on customers' purchases history, and then, convert this profit to the current value based on the company's expected interest rate or return of equity. To do so, we will do as follows:

$$(3)\quad \mathrm{P_i} = \sum_{j=1}^{N} \frac{R_{ij} + C_{ij}}{(1+r)^L}$$

Where,

P_i: is the present value of the customer's profit;

R_{ij}: is the purchase amount of customer i in period j;

C_{ij}: is the gross cost of the organization for the client i in period j;

r: is the interest rate or return on investment for the company; and

L: is the distance between the period j and the current period.

Based on an interview that was conducted with the company's corporate finance office, the average return on investment of about 18% was determined.

As previously stated, the estimated future value of the customer is composed of two dimensions, which are identified with two standard contractual index α and loyalty index β, in this study. In order to consider these two indicators in the CLV calculation, we can use the average value of the customer current benefits.

The average current value of customer benefits can be obtained from the P_i/n relationship, where n is the number of customer purchases in the period under review. Therefore, the *potential value of the customer in future periods* would be:

$$(4)\quad \frac{\mathrm{P_i}}{\mathrm{n}} \times \alpha + \frac{\mathrm{P_i}}{\mathrm{n}} \times \beta = \frac{\mathrm{P_i}}{\mathrm{n}} \times (\alpha + \beta)$$

In this formula $(\alpha + \beta)$ is typically a number between 0 and 2. The index $(\alpha + \beta)$ is the indicator that can best predict the future status of the customer; since, in addition to the probability of a customer's contract renewal in future periods, it also determines the probability of losing a customer. Finally, the CLV can be defined as following:

$$(5)\quad CLV_i = \frac{P_i}{n} \times (\alpha + \beta)$$

Now, the marketing costs for customer retention should also be included in the calculation. The point that is noticeable here is the various marketing channels. Organizations use a variety of promotion channels, such as telephone, fax, gifts and prizes, to communicate with the customer, each with a different cost. In addition, the efficiency of these communication channels is also important. If we define the set-up cost of each communication through the communication channel m with C_m and the frequency with N_m, then we will have:

$$(6)\quad CLV_{\ i} = \frac{P_i}{n} \times (\alpha + \beta)\left[\frac{P_i}{n} - \sum_m C_m \times N_m\right]$$

The above relation has to be extended for prediction modes in subsequent periods. Assuming the number of future periods to predict is k, the CLV calculation formula is presented as follows (Razmi & Ghanbari, 2009):

$$(7)\ CLV_{\ ik} = \sum_{j=1}^{k}\left(\prod_{j=1}^{k}\alpha_{ij} + \prod_{j=1}^{k}\beta_{ij}\right)\left[\frac{P_i}{n_i}\left(\sum_{m=1}^{\infty} C_m \times N_m\right)\right]\frac{1}{(1+r)^{j-1}}$$

Where,

CLV_{ik}: is the customer i lifetime value in the period k;

$0 \le \alpha_{ik} \le 1$: is the probability of purchasing the customer i in the period j;

$0 \le \beta_{ik} \le 1$: is the customer i loyalty index in the period j;

C_m: is cost of marketing unit by communication channel m;

N_m: is the number of marketing channels by communication channel m;

j: is the indicator of estimated period; and,

n_i: is the number of periods that customer i made a purchase.

Phase 3: Clustering the customers based on the lifetime value

In the third phase, customers are clustered based on the value they bring for the organization. For this purpose, fuzzy C-mean algorithm is used in order to obtain more realistic results. Further explanation on fuzzy C-mean algorithm is as follows:

Fuzzy clustering

Clustering is a type of unsupervised learning, a process during which the samples are divided into categories with similar members, also referred to as clusters; in fact it is by clustering techniques that the similar data are identified and implicitly labeled. Clustering methods aim to find similar segments of objects among the input samples. In classic clustering, each sample member belongs to a cluster; in other words, in classic clustering, the clusters do not overlap, whilst in fuzzy clustering, a sample member may belong to more than one cluster. The superiority of fuzzy clustering over the non-fuzzy one in market research has been proved by Hruschka (1986).

Fuzzy C-mean (FCM) clustering algorithm

As in classic C-mean algorithm, in this algorithm also number of clusters (C) needs to be identified beforehand. The target function defined for this algorithm is as follows (Liu, Zhang, & Liu, 2008):

$$J = \sum_{i=1}^{c} \sum_{k=1}^{n} u_{ik}^{m} \, \|x_k - v_i\|$$

Where:

m: is a real number greater than 1, for which 2 is selected in most cases;

X_k: is the kth sample and V_i represents ith cluster or is its center;

U_{ik}: indicates the amount of ith sample's membership in kth cluster;

$|| * ||$: is the amount of sample distance from cluster center in which any function indicating similarity and cluster center may be used.

In U_{ik} it is possible to define a U matrix with c and n as row and column, respectively, with their parameters accepting any value in the

$$\sum_{i=1}^{c} u_{ik} = 1, \forall k = 1, \ldots, n$$

range 0 to 1. If all U matrix parameters are in the form of 0 and/or 1, the algorithm will be similar to a classic C-mean algorithm. While parameters of U matrix may take any value in the range 0 to 1, the sum of parameters of every column should be equal to 1, then we have:

Meaning that the total membership of each sample in cluster c must be equal to 1. Considering the above condition and minimizing the target function we have:

$$u_{ik} = \frac{1}{\sum_{j=1}^{c} \left(\frac{d_{ik}}{d_{jk}} \right)^{2/(m-1)}} \qquad v_i = \frac{\sum_{k=1}^{n} u_{ik}^{m} x_k}{\sum_{k=1}^{n} u_{ik}^{m}}$$

Algorithm steps:

Step 1: Initialized for c, m and U^0, primary clusters are estimated.
Step 2: The centers of the clusters are calculated (v_i).
Step 3: Calculating the membership matrix based on the clusters **calculated in Step 2.**
Step 4: If $||Ul{+}1{-}Ul|| \leq \varepsilon$, then, the algorithm ends; otherwise go to Step 2.

One of the most important issues here is to select the number of suitable clusters. The number of clusters is suitable if: (1) the samples in a cluster are as similar as possible; and (2) samples' membership in different clusters is as dissimilar as possible; or in other words, the clusters' "compactness" should be at maximum and their "separation" should be as big as possible. Both indices should be considered at the same time; otherwise, the optimum number of clusters in maximum compactness mode will be as much as the sample size. On the other hand, the optimum number of clusters in maximum separation mode, would be 1. There are different methods for identifying the number of ideal clusters.

In this paper, we used the Fukuyama and Sugeno method for identifying the validity of the cluster numbers. The algorithm formula is as follows (Wang & Zhang, 2007):

$$S(c)\sum_{k=1}^{n}\sum_{i=1}^{c}(\mu_{ik})^{m}(\|x_k - v_i\|^2 - \|v_i - \bar{x}\|^2)$$

Where:

n: Number of data to be clustered;

c: Number of clusters ($c \geq 2$);

x_k: kth data, usually vector;

$\bar{x}$: Average of data: $x_1, x_2, \dots x_n$;

v_i: Vector expressing the center of ith cluster;

$\| . \|$: norm;

μ_{ik}: Grade of kth data belonging to ith cluster;

m: Adjustable weight (usually $m = 1.5{\sim}3$);

To perform this algorithm in Matlab software, three norms of Euclidean, Manhattan and Mahalonobis have been used to calculate the distance from the cluster center.

Phase 4: Assigning and prioritizing the promotion marketing strategies

In the fourth phase, and after determining the number of optimal clusters of customers, we will be able to prioritize the promotion marketing strategies in each cluster. These strategies include:

1. General advertising: Any impersonal advertising or promotion of ideas, goods or services that is carried out by an advertising unit and involves payment of costs is a non-personal advertising.
2. Personal selling: An oral introduction in the form of face-to-face negotiation with one or more potential purchasers for the purpose of transacting a sale.
3. Sales promotion: Short-term incentives which are used to encourage the purchase or sale of goods and services.
4. Public relations: Establishing favorable relationships with the various communities which deal with the company, through acquisition of good reputation, creation of a "general mental

image" and appropriate treatment, or resolving the issues, rumors, narratives, and unfavorable events (Kotler, 2000).

Through the questionnaire of marketing strategy assessment criteria, the marketing experts were asked to do ranking of 4 Kotler marketing strategies (equal to the number of customer clusters determined in Phase 3) based on 7 assessment criteria for marketing strategies (*Table 1*).

Table 1.Criteria Evaluating Questionnaire

Cluster No: …																						
GUIDANCE: Please especify how well each strategy fits to the seven criteria. Score them with a scale of 1 to 5, which 1 means poor and 5 means excellent.		Tolerability to DMs, leaders, and other stakeholders			Consistency with company's values, culture and mission			Technical feasibility			Cost effectiveness			Client or user impact			Long-term impact			Flexibility or adaptability		
		C1			**C2**			**C3**			**C4**			**C5**			**C6**			**C7**		
Impact																						
Advertising	**A1**																					
Personal selling	**A2**																					
Sales promotion	**A3**																					
public relations	**A4**																					
TOTAL																						

The executive steps in the fourth phase of research are as follows:

I. Determining the criteria to evaluate their promotional strategies and their weights

II. Using Fuzzy TOPSIS technique for allocating strategies to clusters

Step one: Determining the promotional strategies assessment criteria and their weights

In the first step from the fourth phase of the study, marketing experts were asked to determine the criteria for assessing strategies. Following the study of Internet and library references, a total of 13 criteria of the organization's strategy assessments were extracted. Using the Delphi method in order to aggregate the opinions of the marketing experts, they were asked to judge about the importance of the 13 criteria, based on the 7-point Likert scale. Finally, after two rounds, 7 criteria were selected out of 13 (*Table 1*), which their weights were determined as can be seen in *Table 6*.

Step two: Using the fuzzy TOPSIS approach for allocating strategies to clusters

After receiving expert opinions about the weight of each index, we intend to prioritize the four marketing promotional strategies for each cluster of customers using the fuzzy TOPSIS technique.

The TOPSIS method is one of the Multi-Attribute Decision-Making (MADM) methods for ranking of alternatives. This method was first introduced by Hwang and Yoon in 1981. The basis of this method is to select the shortest distance from the ideal solution (a solution that maximizes/minimizes the profit/cost) and the maximum distance from the negative ideal solution (a solution that maximizes/minimizes the cost /profit).

There has been ample of scholars appeared in the literature that concentrated on multi criteria decision making approaches such as TOPSIS which implies high importance of this method in the literature. Among them the works of Chen, (2000), Chen and Hwang(1992), Chu and Lin (2003), Chu (2002), Chu and Lin (2003), Liu et al. (2003) Nemati, Khalafi, and Sarabi (2012), Nemati, Madhoushi, and Safaei Ghadikolaei (2017), Tsaur, Chang, and Yen (2002) can be considered.

Human thoughts are associated with uncertainty and this uncertainty is influential in decision-making. The theory of fuzzy sets as an effective method for dealing with uncertainty, was first proposed by Bellman and Zadeh (1970). The application of fuzzy sets in decision-making issues is one of the most important and efficient applications of this theory in comparison to the classical set theories. In fact, the fuzzy decision theory attempts to model ambiguities and inherent uncertainties existing in preferences, objectives, and constraints existing in decision making.

One of the fuzzy decision-making methods is fuzzy TOPSIS. In this method, the decision matrix elements, or the weight of the indices, or both, are expressed in fuzzy form and with fuzzy numbers.

The steps for doing f-TOPSIS are as follows:

Step 1: Constructing the decision matrix D (a matrix with $m \times n$ dimensions) using fuzzy data

Step 2: Normalizing the decision matrix

Step 3: Calculating weighted normalized matrix

Step 4: determining the Positive Ideal Solution (PIS) and the Negative Ideal Solution (NIS)

Step 5: Calculating the relative distance between each alternative and ideals

Step 6: Ranking of the alternatives.

Results

We dedicated this section to present the results of the four phases that we presented in previous section.

As we mentioned in previous section, we gathered the information of 2000 customers which were selected randomly from MCI SMS VAS database from 7 available services. *Table 2* shows the combination of our randomly selected sample, which were purified by removing the outlier data.

Table 2.The Combination of VAS Customer Sample

VAS type	Customer sample size
Women beauty and health tips	200
Sports news	500
Religious horoscope	200
Joke	100
Hafez horoscope	600
Astrology	200
Successful management daily tips	200
Total	2000

Applying Razmi and Ghanbari's results (2009) for calculating CLV, the results have been depicted in

Table 3 as a sample of calculation.

Table 3.Calculations Related to CLV

MSISDN	Service	$\alpha = T_1/T_2$	$\beta = n/N$	2016			P_i	n	CLV_i
				Cost	Revenue	PV			
989119042378	Joke	0.88	1	163	1,521	1,280	8,963	7	2,407
989174383395	FootballNews	0.13	0.14	23	214	189	1,320	1	356
989147400192	Hafez horoscope	0.13	0.14	23	214	189	1,320	1	356
989194879979	FootballNews	0.88	1	163	1,521	1,280	8,963	7	2,407
989187447299	Joke	0.88	1	163	1,521	1,280	8,963	7	2,407
989169644494	Joke	0.13	0.14	23	214	189	1,320	1	356
989139944828	Joke	0.13	0.14	23	214	189	1,320	1	356
989192473863	FootballNews	0.25	0.29	47	293	242	1,693	2	457
989187237882	FootballNews	0.13	0.14	23	214	189	1,320	1	356
989169677615	Horoscope	0.88	1	163	1,521	1,280	8,963	7	2,407
989126456606	Horoscope	0.88	1	163	1,521	1,280	8,963	7	2,407
989193185411	Astrology	0.63	0.71	115	1,079	921	6,450	5	1,729
989167475913	Horoscope	0.25	0.29	47	293	242	1,693	2	457

In the third phase, customers are clustered based on the value they bring to the organization. For this purpose, fuzzy C-mean algorithm is used in order to obtain more realistic results. *Table 4* shows the results of the calculations of these three methods.

Table 4.Optimum Number of Clusters, by Three Different Criteria

Euclidiant		Manhatan		Mahalanobis	
Iteration	BestClusterNo.	Iteration	BestClusterNo.	Iteration	BestClusterNo.
1	7	1	7	1	8
2	6	2	8	2	9
3	6	3	7	3	6
4	7	4	7	4	9
5	6	5	6	5	8
6	7	6	7	6	9
7	8	7	7	7	12
8	7	8	7	8	15
9	7	9	6	9	7
10	7	10	7	10	8
Median	7	Median	7	11	10
				12	8
				13	9
				14	8
				15	7
				16	7
				17	8
				Median	8

As can be seen, the median of clusters from Manhattan and Euclidean methods was equal to 7, after 10 times execution. Also, the median of clusters after 17 iterations for the Mahalonobis method was equaled to 8, which 8 was chosen as the final number of clusters, due to better separation and higher precision of the Mahalonobis algorithm.

In order to determine the promotional strategy assessment criteria and their weights, experts were asked to determine the criteria for assessing strategies. At the end of the meeting, seven factors were identified as criteria for assessing the strategy. The factors and their weights have been depicted in *Table 5*.

Table 5 The strategy Assessment Criteria and Their Weights

#	Criteria	Weight
1	Tolerability to DMs, leaders, and other stakeholders	0.2
2	Consistency with company's values, culture and mission	0.15
3	Technical feasibility	0.1
4	Cost effectiveness	0.2
5	Client or user impact	0.15
6	Long-term impact	0.1
7	Flexibility or adaptability	0.1
	Sum	**1**

In the final phase, we prioritized marketing strategies to the clusters, using *f*-TOPSIS method. According to steps reviewed in Section 3, we have:

Step 1. The relevant decision matrix to obtain expert opinions about the scores that each strategy receives against the seven criteria is shown in *Table 6* in Cluster 1.

Table 6 Expert Decision Matrix for Cluster 1 (Best Customers)

Cluster: 1		**Criteria**																				
GUIDANCE: Please especify how well each strategy fits to the seven criteria. Score them with a scale of 1 to 5, which 1 means poor and 5 means excellent.		**Tolerability to DMs, leaders, and other stakeholders** C1			**Consistency with company's values, culture and mission** C2			**Technical feasibility** C3			**Cost effectiveness** C4			**Client or user impact** C5			**Long-term impact** C6			**Flexibility or adaptability** C7		
Impact		0.1	0.2	0.3	0.1	0.2	0.3	0.0	0.1	0.2	0.1	0.2	0.3	0.1	0.2	0.3	0.0	0.1	0.2	0.0	0.1	0.2
Advertising	**A1**	7.3	8.0	8.3	8.5	9.0	9.0	7.8	8.0	9.0	7.5	8.0	8.5	7.0	8.0	9.0	6.0	8.0	9.0	6.0	7.0	8.0
Personal selling	**A2**	1.0	1.5	2.0	1.0	2.0	3.5	1.0	2.0	3.0	1.0	1.0	1.5	1.0	1.3	1.8	1.0	1.0	2.0	1.5	2.0	2.5
Sales promotion	**A3**	2.0	3.0	5.0	3.0	4.0	5.0	2.5	4.0	6.0	2.8	3.0	4.0	1.0	2.0	3.5	2.0	3.0	4.0	1.8	2.0	3.0
public relations	**A4**	6.0	7.0	9.0	5.0	7.0	8.0	6.0	7.0	8.0	6.3	7.0	8.5	5.0	6.0	7.0	5.0	6.0	7.0	5.0	6.0	7.0

Step 2. The above decision matrix is normalized by Euclidean norm, which the results are shown in *Table 7*. The blue line indicates the

denominator.

Table 7.Normalized Decision Matrix for Cluster 1 (Best Customers)

Cluster: 1		Criteria																				
		Tolerability to DMs, leaders, and other stakeholders			Consistency with company's values, culture and mission			Technical feasibility			Cost effectiveness			Client or user impact			Long-term impact			Flexibility or adaptability		
		C1			C2			C3			C4			C5			C6			C7		
Impact		9.7	11.1	13.3	10.4	12.2	13.5	10.2	11.5	13.8	10.2	11.1	12.8	8.7	10.3	12.1	8.1	10.5	12.2	8.1	9.6	11.3
Advertising	A1	0.5	0.7	0.9	0.6	0.7	0.9	0.6	0.7	0.9	0.6	0.7	0.8	0.6	0.8	1.0	0.5	0.8	1.1	0.5	0.7	1.0
Personal selling	A2	0.1	0.1	0.2	0.1	0.2	0.3	0.1	0.2	0.3	0.1	0.1	0.1	0.1	0.1	0.2	0.1	0.1	0.2	0.1	0.2	0.3
Sales promotion	A3	0.1	0.3	0.5	0.2	0.3	0.5	0.2	0.3	0.6	0.2	0.3	0.4	0.1	0.2	0.4	0.2	0.3	0.5	0.2	0.2	0.4
public relations	A4	0.4	0.6	0.9	0.4	0.6	0.8	0.4	0.6	0.8	0.5	0.6	0.8	0.4	0.6	0.8	0.4	0.6	0.9	0.4	0.6	0.9

Step 3. Calculating the normalized matrix based on the weight of each of the seven weighted indices, the results of which are shown in *Table 8*.

Table 8 Weighted Normalized Decision Matrix for Cluster 1 (Best Customers)

Cluster: 1		Criteria																				
		Tolerability to DMs, leaders, and other stakeholders			Consistency with company's values, culture and mission			Technical feasibility			Cost effectiveness			Client or user impact			Long-term impact			Flexibility or adaptability		
		C1			C2			C3			C4			C5			C6			C7		
Impact		0.1	0.2	0.3	0.1	0.2	0.3	0.0	0.1	0.2	0.1	0.2	0.3	0.1	0.2	0.3	0.0	0.1	0.2	0.0	0.1	0.2
Advertising	A1	0.1	0.1	0.3	0.0	0.1	0.2	0.0	0.1	0.2	0.1	0.1	0.3	0.0	0.1	0.3	0.0	0.1	0.2	0.0	0.1	0.2
Personal selling	A2	0.0	0.0	0.1	0.0	0.0	0.1	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.1
Sales promotion	A3	0.0	0.1	0.2	0.0	0.0	0.1	0.0	0.0	0.1	0.0	0.1	0.1	0.0	0.0	0.1	0.0	0.0	0.1	0.0	0.0	0.1
public relations	A4	0.0	0.1	0.3	0.0	0.1	0.2	0.0	0.1	0.2	0.0	0.1	0.3	0.0	0.1	0.2	0.0	0.1	0.2	0.0	0.1	0.2

Step 4. After calculating the distance between the positive and negative ideal solutions of the alternatives, the distance of each of the alternatives was calculated from the positive and negative ideal solutions, and the corresponding C_i for each cluster was calculated separately. Finally, we ranked the clusters based on the C_i value. Naturally, a strategy that has a higher C_i than others will be identified

as the top priority for that cluster.

Step 5. At the end, the matrix for assigning strategies to 8 clusters was determined in *Table 9*.

Table 9.Ranking Matrix of Strategies to Each Cluster

Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7	Cluster 8
A1	A1	A4	A4	A4	A3	A2	A2
A4	A4	A1	A3	A3	A2	A3	A3
A3	A3	A3	A2	A2	A4	A4	A4
A2	A2	A2	A1	A1	A1	A1	A1

According to the above table, according to experts' opinions and the use of the TOPSIS technique, the order of prioritizing the promotional strategies for Cluster 1 (the least valuable customers for the organization) is: (a) non-personal advertising, (b) public relations, (c) sales promotion, and (d) non-personal selling.

This means that the most appropriate strategy from experts' point of view for customers, who earn little income, is non-personal advertising through mass media, and the most inappropriate strategy is personal selling.

Accordingly, the prioritization of the promotional strategies for Cluster 8 (the most valuable customers for the organization) is: (a) sales promotion, (b) personal selling, (c) non-personal advertising, and (d) public relations, respectively.

Moreover, as can be seen in *Table 9*, the prioritization of strategies for Clusters 1 and 2 are exactly the same, which means we can merge these two clusters, supposing that these two clusters' customer behavior is similar to each other. The same happens for Clusters 7 and 8, meaning that they can be merged together. So, the number of clusters will be reduced to 6. The final prioritization table of the strategies to the clusters can be depicted in *Table 10*.

Table 10.Final Ranking Matrix of Strategies to Each Cluster

Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
A1	A4	A4	A4	A3	A2
A4	A1	A3	A3	A2	A3
A3	A3	A2	A2	A4	A4
A2	A2	A1	A1	A1	A1

Conclusion

In this paper, we proposed a new practical framework in four phases to deploy more targeted marketing strategies based on CLV in a big mobile operator in Iran. First, the information related to mobile VAS customers, was extracted and purified, based on the CLV definition. Then, the CLV was evaluated from three viewpoints, current value, potential value and customer loyalty, by assigning a lifetime value index to each customer. After that, the customers were clustered based on their CLV, utilizing fuzzy C-mean method. Finally, the appropriate marketing strategy was prioritized for each cluster, by F-TOPSIS method. The validity of the final results were approved and endorsed by the marketing experts and managers of the studied company and they claimed to utilize the proposed framework in marketing activities of the other services such as voice and Unstructured Supplementary Service Data (USSD).

Generally, the applied practical framework can help the telecom companies in better prioritization of their marketing programs, specifically in promotional activities. However, they can use more appropriate and sophisticated methods of CLV calculation, depending on the nature of their industry and availability of their customer data. Also, the proposed model can be used for prioritization of strategies in other marketing mixes such as product, price, and place distribution, as well.

The most important obstacle against our study was the access to customer purchasing data of the studied company. The little history of the VAS customer's data, because of the novelty of such services, was another limitation of the study.

In the future, the research framework of the paper can be used in order to assign or prioritize different strategies in other marketing mixes, such as price, product and placement. Furthermore, other prioritizing solution methods, such as VICOR, Analytic Hierarchy Process (AHP), Analytic Network Process (ANP) and etcetera can be used combined with fuzzy approach, in order to achieve better results, depending on the characteristic of the problem. Also, the researchers can utilize more sophisticated CLV calculation methods, which are more fitted to the business.

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