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Integrating multi-criteria decision making and clustering for business customer segmentation

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Abstract

Purpose – The purpose of this paper is to develop a systematic approach for business customer segmentation.

Design/methodology/approach – This study proposes an approach for business customer segmentation that integrates clustering and multi-criteria decision making (MCDM). First, proper segmentation variables are identified and then customers are grouped by using hierarchical and partitional clustering algorithms. The approach extended the recency-frequency-monetary (RFM) model by proposing five novel segmentation variables for business markets. To confirm the viability of the proposed approach, a real-world application is presented. Three agglomerative hierarchical clustering algorithms namely "Ward's method," "single linkage" and "complete linkage," and a partitional clustering algorithm, "k-means," are used in segmentation. In the implementation, fuzzy analytic hierarchy process is employed to determine the importance of the segments.

Findings – Business customers of an international original equipment manufacturer (OEM) are segmented in the application. In this regard, 317 business customers of the OEM are segmented as "best," "valuable," "average," "potential valuable" and "potential invaluable" according to the cluster ranks obtained in this study. The results of the application reveal that the proposed approach can effectively be used in practice for business customer segmentation.

Research limitations/implications – The success of the proposed approach relies on the availability and quality of customers' data. Therefore, design of an extensive customer database management system is the foundation for any successful customer relationship management (CRM) solution offered by the proposed approach. Such a database management system may entail a noteworthy level of investment.

Practical implications – The results of the application reveal that the proposed approach can effectively be used in practice for business customer segmentation. By making customer segmentation decisions, the proposed approach can provides firms a basis for the development of effective loyalty programs and design of customized strategies for their customers.

Social implications – The proposed segmentation approach may contribute firms to gaining sustainable competitive advantage in the market by increasing the effectiveness of CRM strategies.

Originality/value – This study proposes an integrated approach for business customer segmentation. The proposed approach differentiates itself from its counterparts by combining MCDM and clustering in business customer segmentation. In addition, it extends the traditional RFM model by including five novel segmentation variables for business markets.

Keywords Fuzzy AHP, Multi-criteria decision making, Business customer segmentation, Data clustering

Paper type Case study

1. Introduction

Customer segmentation can be defined as division of a customer base into distinct and internally consistent groups with similar characteristics. It allows companies to develop different marketing strategies according to customer characteristics.

To execute customer segmentation, various techniques and variables are proposed. Clustering, classification, self-organizing maps (SOM), evolutionary algorithms, interaction detection methods and artificial neural network techniques are some of the extensively used segmentation techniques. Among them, data clustering is the most commonly used technique and the components of the recency-frequency-monetary (RFM) model are the most commonly used variables for the customer segmentation (Punj and Stewart, 1983). Data clustering can be defined as the unsupervised classification of observations and it is based on grouping similar observations in the same cluster. RFM model is the numeric expression of customer behaviors and very effective for determining key customers. However, definition and computation of these variables can change depending on the problem (Miglautsch, 2000). For instance, these variables can be defined as: recency, period since the last purchase; frequency, number of purchases made within a certain period; and monetary, total money spent during a certain period.

Many researchers employed RFM model in their segmentation studies. Among them, Chan (2008) segments the customers of an automobile retailer by using genetic algorithm (GA). Chiu *et al.* (2009) proposed a decision support system for market segmentation that integrates conventional statistical analysis and two intelligent clustering methods; SOM and particle swarm optimization (PSO). Cheng and Chen (2009) joined the quantitative value of RFM variables and k-means clustering algorithm into rough set theory. Dhandayudam and Krishnamurthi (2012) suggested a clustering algorithm to overcome the difficulties of traditional clustering algorithms, and segmented the customers of a fertilizer manufacturing company. Wei *et al.* (2013) combined SOM and k-means clustering to segment customers of a hair salon in Taiwan. Deng (2013) proposed an algorithm which is based on k-means clustering, PSO and artificial bee colony to classify customers in e-commerce environment. The reader may refer to Wei *et al.* (2010) for the applications of RFM model.

There exist some other studies extending the RFM model by including additional variables. For instance, Li *et al.* (2011) added "relationship length" variable to traditional RFM model and segmented the customers of a textile manufacturing firm using a two-step clustering method; Ward with k-means. They defined the relationship length as the time between the last and first transaction. However, this definition does not give any information about the repetitiveness of the transactions of a particular customer. Therefore, strength of the relationship should be considered in addition to the relationship length. In addition, Hosseini *et al.* (2010) considered "loyalty" besides the RFM variables. They divided the database into equal quintiles. However, they do not apply any normalization method in their study. In addition, the details on how to obtain the loyalty value were not given. Furthermore, the researchers divided the customer base into 34 clusters, which is impracticable in most cases.

In some segmentation studies, problem-specific variables have been used instead of RFM. For instance, Kim *et al.* (2006) displayed the customers of a wireless telecommunication company with 3D space with axes denoting current value, potential value and customer loyalty and segmented the customers. Teichert *et al.* (2008) applied latent class modeling and segmented airline passengers based on behavioral and socio-demographic variables. Ahn and Sohn (2009) identified customer groups and propose suitable after sales services to these groups. They grouped customers by using fuzzy c-means clustering along with the indicators of customer satisfaction index. Gilboa (2009) segmented Israeli mall customers by using Ward with k-means. In another study, a soft clustering method that uses a latent mixed class membership

clustering approach was developed by Wu and Chou (2011) to group the online consumers of an e-commerce market. Hosseni and Tarokh (2011) implemented a case study on an insurance database. They segmented the customers based on their current value and churn rate. Rajagopal (2011) clustered retail store customers based on variables such as recency, total profit, total revenue and top revenue department. Ho *et al.* (2012) proposed a GA-based *k*-means clustering algorithm to segment the customers of a window curtain manufacturer using the variables of volume, revenue and profit margin per order.

Clustering does not give any information about the importance of customer segments. However, customer value is essential for marketing decisions. Therefore, in some segmentation studies multi-criteria decision making (MCDM) approaches are utilized. In this regard, Liu and Shih (2005) combined group decision making and data mining techniques. They segmented customers based on weighted RFM by using *k*-means. Relative weights of the RFM variables are determined by using analytic hierarchy process (AHP) in the study. The clusters are ranked based on an integrated rating which equals to the weighted sum of RFM values of cluster centroids. In another study, Hosseini *et al.* (2010) segmented customers of a firm based on expanded RFM model. They weighted each variable by eigenvector technique and used *k*-means clustering algorithm to partition the customers into groups. They also obtained the ranking of clusters by considering the distance between center of each cluster with zero point and the integrated rate of each cluster (weighted sum of cluster centers). Table I summarizes the techniques and variables used for customer segmentation problem by the studies considered in our literature survey.

As reported in Table I, customer segmentation is widely studied in consumer markets. However, there is a huge need for systematic approaches for customer segmentation in business markets due to the following reasons. First, as companies have limited resources, they have to use their resources effectively by selecting the valuable customers and making efforts to keep them. In other words, companies should focus on their key customers instead of wasting resources for less profitable customers. Second, number of prospective customers is smaller in business markets and existing customer portfolio is an important reference to gain new customers in the future. Therefore, companies should maintain their market share against potential competitors by providing customized solutions. That is, they should satisfy distinct needs of distinct groups. Third, each and every business customer has special needs. Therefore, closer customer relationship is the key success factor for business markets. However, developing customer-specific strategies is complex and time consuming. Therefore, companies should first segment their customers and then determine the special offerings and priorities in order fulfilling and required degree of relationship for each segment.

As customer segmentation in business markets is quite different from consumer markets, it requires some significant modifications especially in terms of segmentation variables used (Doyle and Saunders, 1985). In consumer markets, customers can be segmented on the basis of their demographics, geography, e.g. country, zone, purchasing behaviors like recency of the last purchase, frequency and monetary value of the purchases, brand loyalty, readiness to buy or their psychographics, i.e. interests, values, attitudes, life styles (Kotler, 2003). Although many of these variables can be applied to business markets, some additional variables related to profit and customer relationship are needed in business market segmentation as today's companies expect an increasing profit stream and long-term partnership with their customers. Therefore, segmentation variables in business markets should be related to purchasing behavior

Article	Customer type	Segmentation variables			Segmentation technique		Ranking of segments
		RFM	Other variables	Variable weighting	Data clustering	Other techniques	
Liu and Shih (2005)	Consumer	*	na	AHP	k-Means	na	Integrated rating
Kim et al. (2006)	Consumer	na	*	na	na	3-D space analysis	Rule based
Teichert et al. (2008)	Consumer	na	*	na	na	Latent class modeling	na
Chan (2008)	Consumer	*	na	na	na	GA	na
Ahn and Sohn (2009)	Consumer	na	*	na	Fuzzy c-means	na	na
Chiu et al. (2009)	Consumer	*	na	na	k-Means	SOM and PSO	na
Gilboa (2009)	Consumer	na	*	na	Ward and k-means	na	na
Cheng and Chen (2009)	Business	*	na	na	k-Means	na	Rule based
Hosseini et al. (2010)	Business	*	*	Eigenvector	k-Means	na	Integrated rating
Wu and Chou (2011)	Consumer	na	*	na	Soft clustering	na	na
Hosseni and Tarokh (2011)	Consumer	na	*	na	na	Rule-based technique	na
Rajagopal (2011)	Consumer	na	*	na	IBM demographic clustering process	na	SQL queries
Li et al. (2011)	Consumer	*	*	na	Ward and k-means	na	na
Dhandayudam and Krishnamurthi (2012)	Consumer	*	na	na	Improved algorithm	na	na
Ho et al. (2012)	Business	na	*	na	k-Means	GA	na
Wei et al. (2013)	Consumer	*	na	na	k-Means	SOM	na
Deng (2013)	Consumer	*	na	na	k-Means	PSO and ABC	Rule based
This study	Business	*	*	Fuzzy AHP	k-Means, ward, single linkage, complete linkage	na	Integrated rating

Note: * denotes the inclusion of the variables

Table I.
The techniques and variables used for customer segmentation

characteristics, competitive characteristics and potential growth characteristics of customers. As the customer who purchases recently and frequently and spends a lot of money through purchases is much more likely to buy again, behavioral characteristics can include recency, frequency, monetary value and volume of purchases. In business markets, length of relationship (LoR) makes a positive impact on customers' loyalty (Reinartz and Kumar, 2000). Therefore, retaining customers over the long run will build a competitive advantage in the market and yield greater profits.

Accordingly, long-term relationship potential and loyalty level of a customer should be used as competitive characteristics in business market segmentation studies. In addition to the relationship length, customers are supposed to show an increasing trend in their purchases in terms of volume and monetary value during the relationship. In this concern, percentage changes in demand and sales revenue can be utilized to represent the potential growth characteristics of the customers.

As clustering achieves only the grouping of similar observations in the same cluster and does not give any information about the relative importance of clusters when multiple variables are of concern, multi-criteria analysis should be combined with clustering by the segmentation approaches to develop more effective customer relationship management (CRM) strategies.

Considering the above mentioned needs and the research gaps, this study proposes a two-step approach for business customer segmentation that integrates clustering and MCDM. The approach extended the traditional RFM model by proposing five additional novel segmentation variables related to business markets namely "loyalty," "average annual demand," "long term relationship potential," "average percentage change in annual sales revenue" and "average percentage change in annual demand." The proposed approach groups customers in a multi-dimensional way by using hierarchical and partitional clustering algorithms.
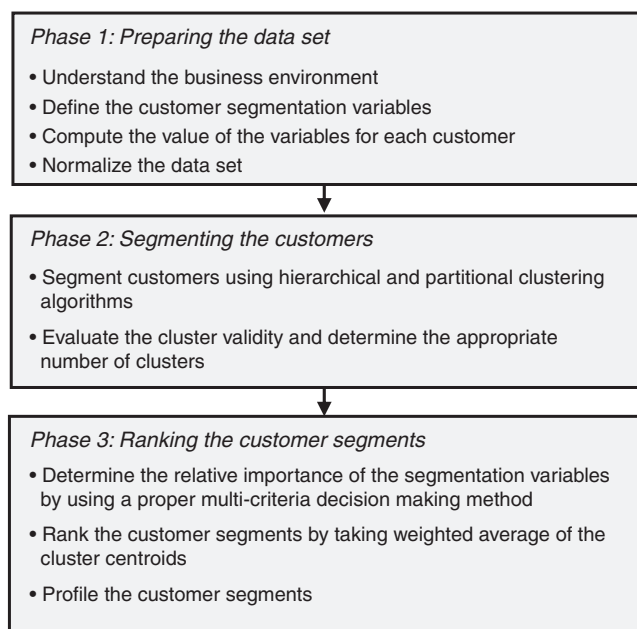
To confirm the viability of the proposed approach, a real-world application is presented in this study. In this regard, business customers of an international original equipment manufacturer (OEM) are segmented. Three agglomerative hierarchical clustering (AHC) algorithms namely "Ward's method," "single linkage" and "complete linkage," and a partitional clustering algorithm, "k-means," are used to segment the customers. To determine the importance levels of the customer segments fuzzy AHP is employed. More specifically, as the importance level of the segmentation variables depends on various factors related to the firms such as sector, competitive position, demand structure, etc., we utilized expert opinions in our application. However, expert judgments based on linguistic assessments and these assessments are often vague and imprecise. To overcome this and provide more realistic solution, we use fuzzy AHP in the application to determine the importance level of the segmentation variables. Finally, segment profiles of the firm are constructed and some CRM strategies are suggested.

The remainder of this study is organized as follows. Section 2 presents the methodological aspects of the study. In this concern, the proposed business customer segmentation approach is presented, and data clustering is briefly explained. Section 2 also explains fuzzy AHP since it is employed in the application of the proposed approach. In Section 3, computational experiments are provided. Finally, conclusions and future research directions are presented in Section 4.

2. The proposed approach and theoretical background

2.1 The proposed approach

As illustrated in Figure 1, the proposed business customer segmentation approach includes three phases namely "preparing the data set," "segmenting the customers" and "ranking the customer segments." Phase 1 starts with understanding the business environment. Then, segmentation variables are defined and their values are computed for each customer. In the next step, data set is normalized. In phase 2, customers are segmented by using hierarchical and partitional clustering algorithms. Additionally, validity of the clusters is evaluated and the appropriate number of clusters is determined.

Phase 1: Preparing the data set

- Understand the business environment
- Define the customer segmentation variables
- Compute the value of the variables for each customer
- Normalize the data set

Phase 2: Segmenting the customers

- Segment customers using hierarchical and partitional clustering algorithms
- Evaluate the cluster validity and determine the appropriate number of clusters

Phase 3: Ranking the customer segments

- Determine the relative importance of the segmentation variables by using a proper multi-criteria decision making method
- Rank the customer segments by taking weighted average of the cluster centroids
- Profile the customer segments

Figure 1.
The proposed
business customer
segmentation
approach

Finally, in phase 3, importance of the proposed segmentation variables are determined by using a proper multi-criteria decision-making method. Consequently, the customer segments are ranked by taking weighted average of the cluster centroids and then they are profiled.

2.2 Data clustering
Clustering is an unsupervised learning technique and can be defined as division of a heterogeneous population into more homogenous groups. It has various applications including customer segmentation, image segmentation, information retrieval, web pages grouping and scientific and engineering analyses (Pham and Afify, 2007). Typical clustering activity involves the following steps:

- data representation;
- definition of a proximity measure appropriate to the data domain;
- grouping;
- data abstraction; and
- assessment of output.

Clustering algorithms can be classified as hierarchical and partitional. As stated previously, we employ both hierarchical and partitional algorithms in this study to divide the customer base. The hierarchical algorithms can be classified as agglomerative and divisive based on a bottom-up or top-down decomposition. In AHC, initially each data point is a distinct cluster then these clusters are merged until all data points combined in a single cluster. The most commonly used AHC algorithms are "single linkage," "complete linkage," "average linkage" and "Ward's method" (Punj and Stewart, 1983). In single linkage clustering, two separate clusters that have the shortest distance are combined. Herein, distance between two clusters is the distance between the most similar members of the clusters. However, it can sometimes

cause clustering some heterogeneous data points together. In addition, complete linkage clustering is sometimes called farthest neighbor approach. Like single linkage clustering, two separate clusters that have the shortest distance are combined by this algorithm. However, in complete linkage clustering, distance between two clusters is the distance between the most dissimilar members of the clusters. Moreover, Ward's method (Ward, 1963) combines the clusters based on the optimal objective function value. This algorithm considers the clustering problem as an analysis of variance problem and objective function is often defined as minimization of the sum of squared error.

Unlike AHC, in partitional clustering, initially all data points constitute a single cluster. Then this cluster is successively divided into clusters till one data point remains in each cluster. Partitional algorithms partition the database into a set of k clusters so that it optimizes the chosen criterion. "k-means" is a well-known partitional clustering algorithm and finds a partition such that the squared error within clusters is minimized. The algorithm is based on assigning each data point to its nearest centroid, and it proceeds as follows:

Step 1. Determine the number of clusters (k).

Step 2. Randomly assign k data points to be the initial cluster centroids.

Step 3. Assign each data point to a cluster that has the nearest centroid.

Step 4. Recalculate the cluster centroids.

Step 5. Repeat steps 3 to 5 until termination.

One of the major problems in cluster analysis is termination of the algorithm or in other words determining the number of clusters. The ideal number of clusters is the level of minimum variation within clusters and the maximum variation between clusters. However, the final decision on the number of clusters is left to decision maker (Dubes, 1993). Statistical approaches that use optimality of a specific criterion are often utilized for this purpose. The most commonly used cluster validity indices are *Dunn, Davies Bouldin, Silhouette, Sum of Squares within cluster (SSWC), C, Calinski-Harabasz* (Rendon *et al.*, 2011).

In this study, SSWC is used as the cluster validity index. SSWC is a simple and the most widely used criterion to evaluate the validity of clustering results and determine the number of clusters. SSWC is formulated as follows:

$$SSWC = \sum_{k=1}^{K} \sum_{\forall x_i \in C_k} \left(x_i - \mu_k \right)^2 \tag{1}$$

where K denotes the number of clusters; C_k is the set of instances in cluster k; μ_k is the vector mean of cluster k. Smaller value of SSWC indicates a "better" clustering solution. SSWC and sum of squares between clusters (SSBC) is a constant that is equal to the total sum of squares (TSS), which is the sum of squares of the distance of each point to the overall mean of the data (see, Equations (2) and (3)). It means that minimizing SSWC is equivalent to maximizing SSBC:

$$TSS = SSWC + SSBC \tag{2}$$

$$TSS = \sum_{k=1}^{K} \sum_{\forall x_i \in C_k} \left(x_i - \mu_k \right)^2 \tag{3}$$

where K denotes the number of clusters, C_k is the set of instances in cluster k, and μ is the vector mean of data set.

2.3 Fuzzy AHP

Today, decision makers confront with many complex decision problems and they often use multiple criteria to handle these problems. AHP is one of the most widely used MCDM tools and has been applied in a wide variety of areas. Sipahi and Timor (2010) presented a literature review of recent applications of AHP, and categorized the studies according to the application area such as manufacturing, environmental management and agriculture, general decision problem, power and energy industry, transportation industry, construction industry, health and others. Some review studies focussed on the application of AHP in specific fields such as marketing (Mark, 2001), energy (Pohekar and Ramachandran, 2004), medical and healthcare decision making (Liberatore and Nydick, 2008). The reader may refer to Subramanian and Ramanathan (2012) for a review of the applications of AHP in operations management.

In AHP, decision maker's knowledge is represented with crisp values. However, human judgments are usually based on unclear linguistic assessments and it is not realistic to represent them with crisp values. In addition, people may have difficulties arranging competing alternatives consistently if two or more criteria have to be taken into account (Fiarni *et al.*, 2013).

To deal with uncertainty of human thought, Zadeh (1965) first introduced the fuzzy set theory, which was oriented to the rationality of uncertainty due to imprecision or vagueness. A fuzzy set is a class of objects with a continuum of grades of membership. Such a set is characterized by a membership function, which assigns to each object a grade of membership ranging between zero and one. Triangular fuzzy numbers (TFNs) are the most commonly used fuzzy numbers and a TFN, $\tilde{M}$, is denoted as $M = (l, m, u)$ as illustrated in Figure 2. The parameters l, m, and u, respectively denote the smallest possible value, the most promising value and the largest possible value that describe a fuzzy event (Kahraman *et al.*, 2004).

Fuzzy AHP is an effective tool for solving MCDM problems. It has been extensively used in various fields such as location selection (Kuo *et al.*, 2002), supplier selection (Kahraman *et al.*, 2003; Chan *et al.*, 2008), project selection (Enea and Piazza, 2004; Huang *et al.*, 2008), machine tool selection (Ayağ and Özdemir, 2006; Duran and Aguilo, 2008) and personnel selection (Güngör *et al.*, 2009). The main advantage of this method is that it reflects the human reasoning and thinking style by making allowances for the vagueness and imprecision of human judgments. Different from classical AHP, pair-wise comparisons are represented by fuzzy numbers in fuzzy AHP. There exist several fuzzy comparison methods proposed by researchers. For instance, Van Laarhoven and
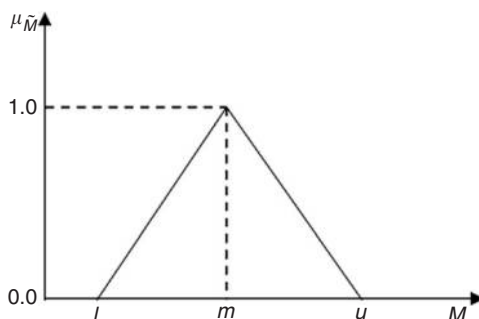
Figure 2.
A triangular
fuzzy number

Pedrycz (1983) proposed a fuzzy logarithmic least squares method to obtain triangular fuzzy weights from a fuzzy comparison matrix. Buckley (1985) used geometric mean method to calculate the fuzzy weights. Csutora and Buckley (2001) proposed λ-max method, which is the direct fuzzification of the λ-max method. Mikhailov (2003) proposed a fuzzy preference programming method that computes crisp weights from fuzzy comparison matrices. Chang (1992) introduced an extent analysis method that derives crisp weights from fuzzy pair-wise comparison matrices.

In this study, Chang's (1992) extent analysis method is used for weighting the customer segmentation variables. According to this method, each object is taken from an object set $X = \{x_1, x_2, ..., x_n\}$ and extent analysis for each goal, g_i, in a goal set $U = \{u_1, u_2, ..., u_m\}$ is performed. Computational procedure of Chang's (1992) extended fuzzy AHP is described as follows:

Step 1. The value of fuzzy synthetic extent value with respect to the ith criterion is defined by the following equation:

$$S_i = \sum_{j=1}^{m} M_{gi}^j \otimes \left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^j \right]^{-1} \qquad (4)$$

where all $M_{gi}^j (j = 1, 2, ..., m)$ are TFNs.

Step 2. As $M_1 = (l_1, m_1, u_1)$ and $M_2 = (l_2, m_2, u_2)$ are TFNs, the degree of possibility of $M1 \geqslant M2$ is defined as:

$$V(M_1 \geqslant M_2) = \begin{cases} 1, & \text{if } m_1 \geqslant m_2 \\ 0, & \text{if } l_2 \geqslant u_1 \\ \frac{l_2 - u_1}{(m_1 - u_1) - (m_2 - l_2)}, & \text{otherwise} \end{cases} \qquad (5)$$

Step 3. To compare M_1 and M_2, we need both the values of $V(M_1 \geqslant M_2)$ and $V(M_2 \geqslant M_1)$. The degree of possibility for a convex fuzzy number to be greater than k convex fuzzy numbers $M_i(i = 1, 2, ..., k)$ can be defined as follows:

$$V(M \geqslant M_1 M_2 M_3, ..., M_k) = V[(M \geqslant M_1) \text{ and } (M \geqslant M_2 \text{ and } .. \text{ and } (M \geqslant M_k))]$$
$$= \min V(M \geqslant M_i), \quad i = 1, 2, ..., k. \qquad (6)$$

Assume that $d'(A_i) = \min V(S_i \geqslant S_k)$ for $k = 1, 2, ..., n; k \neq i$ then the weight vector is given by Equation (7):

$$W' = \left(d'(A_1), d'(A_2), ..., d'(A_n) \right)^T \qquad (7)$$

where $A_i(i = 1, 2, ..., n)$ are n elements.

Step 4. Via normalization, the normalized weight vectors are presented in Equation (8) where W is a non-fuzzy number:

$$W = (d(A_1), d(A_2), ..., d(A_n))^T \qquad (8)$$

3. Application of the proposed approach
3.1 The case company and data set
In business markets, most of the leading brands take the advantage of the economies of scale by collaborating with OEMs. In today's highly competitive markets, becoming

a successful OEM necessitates deeper understanding of customers and satisfying their needs. Therefore, OEMs should segment their customers to make better operational, tactical and strategic decisions.

The case company is one of the successful OEMs over the world and it has an integrated TV production process extending from the production of electronic cards to the final assembly. The company has a wide export network and it produces TVs both for its own brand and also for many other worldwide electronic companies. In this study, we focus on the business customers of the company and divide the business customer base into discrete customer groups and find the relative importance of them. Customer transaction data are extracted from the enterprise resource planning system of the company. In this regard, 28,840 records of 317 customers between January 2002 and December 2011 are analyzed.

3.2 Definition of the segmentation variables

Customers of a company should be evaluated according to their special characteristics. Types of data held about customers vary across industries and even across companies. For instance, industries like fast moving consumer goods, retail, financial services and telecommunication have a rich customer database that can be utilized in making effective CRM policies. On the other hand, companies in business markets generally have relatively limited information about their customers. Therefore, business customer assessments differ from one industry to another. At this point, both business understanding and market analysis become vital for customer segmentation.

In this study, we propose five novel segmentation variables for business markets namely "loyalty," "average annual demand," "long term relationship potential," "average percentage change in annual demand" and "average percentage change in annual sales revenue." In our application, these five variables and the RFM variables are used for business customer segmentation. Definitions of these variables are presented in the following.

V1: recency. Recency can be described as the date of last transaction of a specific customer within the observation period. Recent order indicates that the relationship is live. The value of recency is scaled from 1 to 7 and it equals to 1 for 2005 and 7 for 2011.

V2: loyalty. The term customer loyalty is the behavior of repeat customers. Customers can be said "loyal" when they consistently purchase a certain product or brand over a long period of time. In this study, loyalty value is calculated by Equation 9, where active years corresponds to total number of years that transactions were conducted by a specific customer during its LoR. LoR is the number of years between the first transaction of a specific customer and the end of the observation period (2011). The reason for multiplying the ratio of active years to LoR by active years is to distinguish between loyalty values of customers whose active years equal to their LoR:

$$Loyalty = \frac{(Active\ years)^2}{LoR} \tag{9}$$

V3: average annual demand (AAD). The value of this variable is calculated by averaging demand of a customer during its LoR with the company. In other words, it is the ratio of total demand to LoR. The reason to use this variable is to calculate comparable values for each customer with respect to total demand.

V4: average annual sales revenue (AASR) (monetary value). This variable can be defined as the average expenditure of a customer made during its LoR. It is the ratio of total sales revenue to LoR.

V5: frequency. Frequency indicates the average number of transactions conducted per year. It is computed by multiplying the ratio of total number of months in which at least a transaction was conducted to total number of months between the first transaction and the end of observation period by 12.

V6: long-term relationship potential (LTRP). Long-term relationship simply means building customer loyalty for the company. It is thought that if a customer works with the company for a long time or in other words its loyalty is high and at the same time has a recent order we may assume that this customer will keep working with this company in the future. Long-term relationship potential is calculated as a score by the following equation:

$$LTRP = Loyalty \times Recency \tag{10}$$

V7: average percentage change in annual demand (APCIAD). Not only the amount of but also the variation in annual demand of a specific customer is important for companies. Therefore, a variable that indicates the average percentage change in annual demand is necessary. With this variable, we can see whether the annual customer demand increases or decreases. If we consider demand values in two consecutive years, respectively a and b, APCIAD is calculated as $(b-a)/a$. This variable equals to zero for customers whose first transaction was conducted in 2011.

V8: average percentage change in annual sales revenue (APCIASR). This variable is the measure of change in annual sales revenue. By evaluating the value of APCIASR, we can see whether the annual sales revenue obtained from a particular customer increases or decreases. If we consider sales revenues of two consecutive years, respectively, c and d, APCIASR is calculated by $(d-c)/c$ for each customer.

After computing values of these eight variables for each customer, initial data set is obtained and then normalized by using min-max normalization (standardization) between 0 and 1 to create a common scale for the variables and make them commensurate. The summary statistics are presented in Table II.

3.3 Segmenting the customers

In our application, we used Euclidean distance as dissimilarity metric and employed three AHC algorithms, which are "Ward's method," "single linkage" and "complete linkage," and a partitional clustering algorithm, "k-means," to segment the customers. As recalled,

| Variable	Observations	Min.	Max.	Mean	SD
V1	317	0.000	1.000	0.812	0.236
V2	317	0.000	1.000	0.220	0.233
V3	317	0.000	1.000	0.023	0.100
V4	317	0.000	1.000	0.026	0.103
V5	317	0.000	1.000	0.298	0.302
V6	317	0.000	1.000	0.216	0.232
V7	317	0.000	1.000	0.064	0.099
V8	317	0.000	1.000	0.018	0.061

Table II.
Summary statistics of the data set

the aim of this study is to divide customer base into manageable number of groups. Determining the number of clusters is important for the management of these groups. Increasing the number of clusters makes the management more difficult. As known, number of customers is smaller in business markets compared to consumer markets and business customers' behaviors vary less than consumers' behaviors. Therefore, we determine the number of clusters as three, five and seven in our application.

Application results of the clustering algorithms are presented in Table III. The results reveal that "k-means" provides superior results in terms of *SSWC* than those of the other methods. After determining the best method, we should also determine the number of clusters. It is obvious that when the number of clusters increases, *SSWC* decreases. The clustering with small number of clusters and low value of *SSWC* is treated as adequate. Figure 3 visualizes *SSWC* values for the clustering algorithms for different number of clusters. The results indicate that *SSWC* value of *k*-means algorithm is subject to small changes for the number of clusters bigger than five. Accordingly, we conclude that segmenting the customers into five clusters is proper.

Clustering algorithm	No. of clusters	SSWC	SSBC	TSS	SSWC/TSS
Ward's method	3	37.111	54.295	91.406	0.406
Ward's method	5	23.777	67.628	91.406	0.260
Ward's method	7	17.389	74.017	91.406	0.190
Single linkage	3	87.226	4.180	91.406	0.954
Single linkage	5	81.470	9.936	91.406	0.891
Single linkage	7	80.076	11.329	91.406	0.876
Complete linkage	3	61.218	30.188	91.406	0.670
Complete linkage	5	32.055	59.351	91.406	0.351
Complete linkage	7	29.783	61.623	91.406	0.326
k-Means	3	35.303	56.103	91.406	0.386
k-Means	5	22.996	68.410	91.406	0.252
k-Means	7	17.212	74.194	91.406	0.188

Table III.
Application results
of the clustering
algorithms
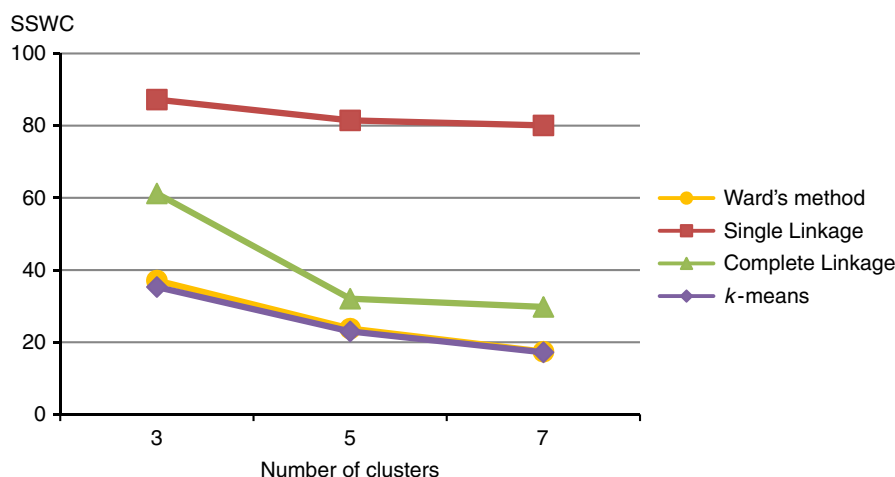
Figure 3.
SSWC values of the
clustering algorithms

Table IV presents the centroid, rank and size of each cluster that is generated by
k-means method. Further, Figure 4 visualizes the group averages for each variable.

3.4 Determining the importance of the segmentation variables
In our application, fuzzy AHP approach is employed to determine the importance
of the segmentation variables. Each variable is evaluated by the sales supervisor
through stating the importance of the variables using linguistic variables and filling
the pair-wise comparison matrix L (see Table V) that is defined as a set of linguistic
values. $L = \{$VHI, HI, SHI, M, SLI, LI, VLI$\}$, where VHI = very high important,
HI = high important, SHI = somewhat high important, M = medium, SLI = somewhat

Cluster	V1	V2	V3	V4	V5	V6	V7	V8	Number of customers
1	0.995	0.174	0.036	0.037	0.627	0.184	0.083	0.017	61
2	0.83	0.114	0.001	0.001	0.097	0.11	0.035	0.008	109
3	0.98	0.49	0.014	0.018	0.492	0.488	0.101	0.037	67
4	0.424	0.04	0.001	0.001	0.045	0.024	0.033	0.008	68
5	0.986	0.935	0.342	0.372	0.811	0.925	0.21	0.056	12

Table IV. Results of *k*-means algorithm corresponding to five clusters
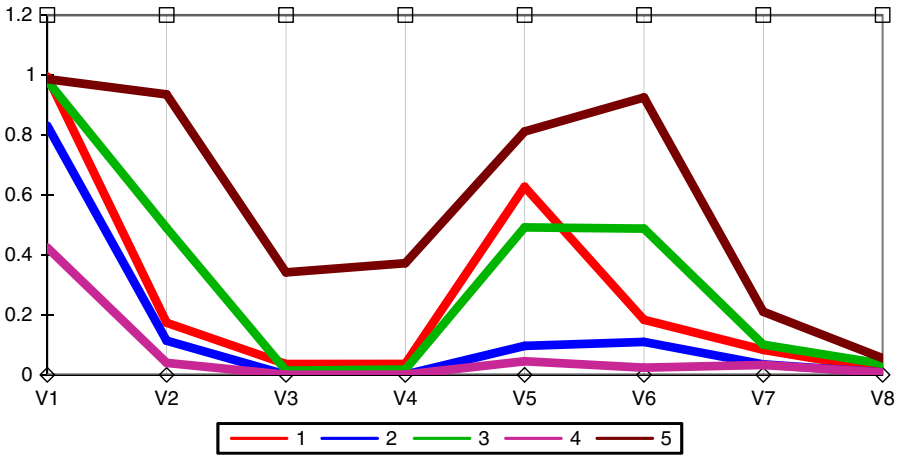
Figure 4. Profile plot of clusters obtained by *k*-means method

	V1	V2	V3	V4	V5	V6	V7	V8
V1	M	SLI	LI	LI	SHI	SLI	SHI	M
V2	SHI	M	SLI	LI	SHI	SLI	SHI	M
V3	HI	SHI	M	SLI	HI	SHI	SHI	SHI
V4	HI	HI	SHI	M	HI	SHI	HI	SHI
V5	SLI	SLI	LI	LI	M	M	SLI	M
V6	SHI	SHI	SLI	SLI	M	M	HI	SHI
V7	SLI	SLI	SLI	LI	SHI	LI	M	SLI
V8	M	M	SLI	SLI	M	SLI	SHI	M

Table V. Pair-wise comparison matrix

low important, LI = low important and VLI = very low important. Linguistic values and corresponding TFNs are presented in Table VI.

The weight vector is obtained as $W' = (0.292, 0.456, 0.833, 1, 0.113, 0.653, 0.128, 0.4)$. Then, the normalized weight vector is computed as $W = (0.075, 0.118, 0.215, 0.258, 0.03, 0.168, 0.033, 0.103)$. The results indicate that the most important variable is AASR while the least important variable is frequency. The reason why the frequency is the least important variable is related with the industry in which the company operates. The company produces TV that is a kind of durable consumer goods, and both production and distribution processes are long and costly. In addition, most of the customers located in geographically dispersed countries over the world and they are far from the production facility. Therefore, the company prefers less frequent, high volume orders instead of frequent and low-volume orders to avoid high setup, production and distribution costs.

Importance levels of the clusters are determined by taking weighted average of the cluster centroids obtained in Section 3.3. Table VII indicates the weighted average of cluster centroids, ranks and sizes of clusters.

3.5 Evaluation of the results

We segment 317 business customers of the OEM as "best," "valuable," "average," "potential valuable" and "potential invaluable" according to the cluster ranks obtained in Section 3.4. Characteristics of these segments are summarized in Table VIII.

The results reveal that "Cluster five" (best customers) is the most important segment. With respect to "AAD," "AASR" and "LTRP" variables, this cluster has the greatest values among the clusters. The customers in this segment are totally loyal customers and they order products with high volumes. In addition, these customers are the most important source of income for the company. Therefore, they should be retained. Also, some portion of capacity should be reserved for these customers in anticipation of their urgent demands. Further, these customers should have higher priority in order fulfilling.

Linguistic variable	TFN
Very low important (VLI)	(0, 0, 0.10)
Low important (LI)	(0.05, 0.15, 0.25)
Somewhat low important (SLI)	(0.20, 0.325, 0.45)
Medium (M)	(0.40, 0.50, 0.60)
Somewhat high important (SHI)	(0.55, 0.675, 0.80)
High important (HI)	(0.75, 0.85, 0.95)
Very high important (VHI)	(0.90, 1, 1)
Source: Belmokaddem *et al.* (2009)	

Table VI.
Linguistic variables
and corresponding
TFNs

Cluster	Weighted average of cluster centroid	Rank	Number of customers
1	0.166	3	61
2	0.100	4	109
3	0.243	2	67
4	0.044	5	68
5	0.546	1	12

Table VII.
Results of *k*-means
algorithm
corresponding to
five clusters

		V1	V2	V3	V4	V5	V6	V7	V8
					Segmentation variables				
Cluster 1 average	Avg.	0.667	0.094	0.000	0.000	0.291	0.106	0.021	0.006
	Max.	0.995	0.174	0.036	0.037	0.627	0.184	0.083	0.017
	Min.	1.000	0.321	0.858	0.700	1.000	0.330	0.448	0.084
Cluster 2 potential valuable	Avg.	0.667	0.018	0.000	0.000	0.011	0.021	0.000	0.000
	Max.	0.830	0.114	0.001	0.001	0.097	0.110	0.035	0.008
	Min.	1.000	0.343	0.006	0.012	0.295	0.352	0.712	0.094
Cluster 3 valuable	Avg.	0.667	0.321	0.000	0.001	0.128	0.301	0.009	0.003
	Max.	0.980	0.490	0.014	0.018	0.492	0.488	0.101	0.037
	Min.	1.000	0.786	0.188	0.261	1.000	0.679	0.563	1.000
Cluster 4 potential invaluable	Avg.	0.000	0.000	0.000	0.000	0.000	0.000	0.019	0.005
	Max.	0.424	0.040	0.001	0.001	0.045	0.024	0.033	0.008
	Min.	0.500	0.182	0.004	0.007	0.312	0.090	0.162	0.033
Cluster 5 best	Avg.	0.833	0.547	0.020	0.022	0.595	0.553	0.049	0.009
	Max.	0.986	0.935	0.342	0.372	0.811	0.925	0.210	0.056
	Min.	1.000	1.000	1.000	1.000	0.981	1.000	1.000	0.366

Table VIII.
Characteristics of
the final segments

Cluster three (valuable customers) is the second important customer segment. This segment is also an important source of income for the company. The customers in this segment have a long relationship with the company, they have great volume of orders and their orders are generally recent. In addition, they show an increasing trend in AAD and AASR. Therefore, they have high potential for long-term relationships with the company. Cluster one (average customers) is the third important segment. Customers in this segment have an average LoR with the company. They are partially loyal to the company, they have average amount of orders and their LTRP is moderate. Accordingly, the company should make an effort to increase the sales volume of the customers in this segment. Cluster two (potential valuable) is the fourth important segment. Most of the customers in this segment are new customers. Although they have shorter relationship with the company, it can be stated that they have great amount of annual demand. Therefore, the company should focus on developing the relationship with the customers in this segment. Cluster four (potential invaluable) is the fifth important segment. Most customers in this segment do not have recent orders and their relationships with the company are inactive. They have low-volume orders, and accordingly the revenue obtained from them is low. Therefore, they can be qualified as disloyal. In addition, some of them are relatively new customers but they have lower annual demand than the new customers in cluster two. Consequently, relationship with these customers should be reconsidered attentively.

4. Conclusions

This study proposes an integrated approach for business customer segmentation. The proposed approach differentiates itself from its counterparts by combining MCDM and clustering in business customer segmentation. In addition, it extends the traditional RFM model by including five novel segmentation variables for business markets namely "loyalty," "average annual demand," "long term relationship potential," "average percentage change in annual demand" and "average percentage change in annual sales revenue."

The proposed approach groups customers in a multi-dimensional way by using hierarchical and partitional clustering algorithms. As clustering does not give any information about the relative importance of clusters when multiple variables are of concern, multi-criteria analysis is combined with clustering by the proposed approach to develop more effective CRM strategies.

To prove the practicality of the proposed approach, a real-world application is presented in this study. Business customers of an international OEM are segmented in the application. Three AHC algorithms namely "Ward's method," "single linkage" and "complete linkage," and a partitional clustering algorithm, "k-means," are employed in the segmentation. To determine the relative importance of the customer segments fuzzy AHP is utilized as the MCDM approach. Thus, imprecise assessments of experts are effectively reflected to the decision process. Finally, segment profiles of the case company are constructed and some CRM strategies are suggested. The results of the application reveal that the proposed approach can effectively be used in practice for business customer segmentation. By making customer segmentation decisions, the proposed approach can provides firms a basis for the development of effective loyalty programs and design of customized strategies for their customers. Thus, it can contribute to gaining sustainable competitive advantage in the market.

In practice, customer base, customer segmentation variables and their importance levels are subject to change over time. Therefore, customer segments should be updated dynamically.

The success of the proposed approach relies on the availability and quality of customers' data. Therefore, design of an extensive customer database management system is the foundation for any successful CRM solution offered by the proposed approach. Such a database management system may entail a noteworthy level of investment.

Any future study might apply the clustering algorithms by using different similarity/dissimilarity metrics. In addition, adaptation of the proposed segmentation variables to the consumer markets can be stated as a future research subject.

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