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RFM-Based customer segmentation as an elaborative analytical tool for enriching the creation of sales and trade marketing strategies

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Abstract

In the current intensified competitive market, analyzing customers meticulously and implementing customer relationship management accordingly are the main reasons behind the success of breakthrough companies. One of the main constraints and deficiencies of sales and trade marketing departments in terms of sales development in FMCG (fast moving consumer goods) industry is that they don't know which customer segments to target and how to deal with each one. In this study we discuss how these departments can gather customer data and how they can analyze these data to gain useful customer insights. We provide an overview of customer segmentation based on RFM method and customer lifetime value (CLV). The results would be useful for sales, trade marketing and marketing decision-makings in all industries specially the active companies in FMCG industry.

Keywords: RFM-Based customer segmentation, trade marketing strategies

Introduction:

In a time of cost-cutting and intensive competitive environments, it becomes of great importance for companies to fully exploit their existing customer base and developing the depth and the surface of total sales. Moreover, when the future duration of the relationship between customers and the company is at risk, it is important to detect the customers decreasing loyalty to the company (churners). Consequently, customer retention and revitalization campaigns are implemented.
Most sales managers and marketers have difficulty in identifying the right customers to engage in successful sales and trade marketing campaigns. So far, customer segmentation is a popular method that is used for selecting appropriate customers for launching a campaign. Unfortunately, the link between customer segmentation and sales and trade marketing campaign is missing. Another problem is that sales

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managers and marketers generally use different models to conduct customer segmentation and customer targeting. This study presents a new approach that combines customer targeting and customer segmentation for trade marketing and sales strategies, using the transaction history of a customer with the company. This investigation identifies customer behavior using a recency, frequency and monetary (RFM) model and then uses a customer life time value (CLV) model to evaluate proposed segmented customers to be dealt with trade marketing and sales strategies accordingly. But it should be mentioned that for sales and trade marketing managers, segmentation should not the end in itself, but rather a mean to an end (Jonker, Piersma, & Poel, 2004).

Three purposes involved in this study are as the following: (1) explain a new analytical tool for customer segmentation (2) cluster customer value as output (customer loyalty) that is classified into 8 segments (3) find out the characteristics of each segment in order to optimize sales, trade marketing and CRM strategies. The result of this study could be as a guideline for sales and trade marketing strategists, for each customer segment, and increasing the depth and the surface sales for the most valuable customer groups. This work devises an approach for dealing with customer segmentation problems in FMCG industry.

Literature Review:

Many companies are currently operating in an intensified competitive environment, shortening product life cycles and decreasing customer brand loyalty (Cooil, Keiningham, Aksoy, & Hsu, 2007). In an effort to tighten the relationship that exists with a customer, many companies increasingly turn to the concepts of Customer Relationship Management (CRM) (Reinartz & Kumar, 2002; Winer, 2001) and, more specifically, database marketing.

It is so important and vital for firms to know different types of customers to make decisions more profitably. Knowing customers one by one in some businesses is not easy, so using customer segmentation method could be useful to solve this limitation. Nowadays customer segmentation based on their value or their lifetime value is being used instead of customer need-based segmentation. Customer lifetime value includes calculating past and present value of the customers and predicting the future value of the customers using data mining techniques.

In the recent years, data mining has not only a great popularity in research area but also in commercialization. Data mining can help organizations discovering meaningful trends, patterns and correlations in their customer, product, or data, to drive improved customer relationships and then decrease the risk of business operations (Witten & Frank, 2005).

For a successful business, sales and trade marketing manager, engaging in an effective campaign is a key task. Traditionally, sales and trade marketing managers must first identify market segmentation using a mathematical mode and then implement an efficient campaign plan to target profitable customers (Fraley & Thearting, 1999).

This process confronts considerable problems. First, most previous studies used various mathematical models to segment customers without considering the correlation between customer segmentation and a campaign. Previously, the link between customer segmentation and campaign activities was most manual or missing (Fraley & Thearting, 1999). From an academic perspective, the processes of customer segmentation should consider the constraints or dependent variables of campaign activities in attempting to increase the relevancy of both processes.

In most previous studies, the quality of a segmentation methodology is measured based on within-segment and inter-segment heterogeneity (Wedel & Kamakura, 2000). Realistically, sales managers and marketers are concerned with and interested in maximizing the net value of targeted customers, rather than caring about within-segment homogeneity or targeting rate (Jonker et al., 2004; Kim, Street, Russell, & Menczer, 2005). To solve the core problem of marketers facing, this investigation applies a customer

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life time value model to assess the fitness between targeted customer groups and marketing strategies, rather than measuring the within segment homogeneity.

Each year numerous empirical researches are published dealing with this area. Each study brings its own advantages and efforts to solve segmentation problems. In most marketing studies, customer segmentation is designed to increase customer value or profitability through careful customer targeting. (Chan, 2005; Chung et al., 2004; Hwang et al., 2004; Jones et al., 2006; Kim & Street, 2004; Kim et al., 2005; Kuo et al., 2006; Shin & Sohn, 2004; Woo et al., 2005). To achieve such a goal, the CRM research team of IBM corporation proposes 2W (What, Whom) and 1H (How) as three key factors in delivering customer value (Liu, 2001)

An important discipline within database marketing is customer retention management, or the prevention of customer churn, defined as the propensity of customers to end the relationships with the company, and to switch to other suppliers. Several authors report the close link between customer retention and firm profitability (Gupta, Lehmann, & Stuart, 2004; Larivière & Van den Poel, 2005). Moreover, it is generally accepted that prolonging relationships with existing customers generates a higher return on investment than attracting new customers (Mozer, Wolniewicz, Grimes, Johnson, & Kaushansky, 2000; Rust & Zahorik, 1993). A well-documented approach to improve customer retention is the practice of customer churn prediction, in which a classification model is built to identify those customers that are most likely to demonstrate churning behavior (Xie, Li, Ngai, & Ying, 2009).

Strong classification performance is generally perceived as a vital element of a customer churn prediction model. While Neslin, Gupta, Kamakura, Lu, and Mason (2006) indicate that several steps within the modeling process determine the success of a churn prediction project, they emphasize that the estimation technique has a considerable impact upon the return of investment of retention actions.

Consequently, a large body of literature is devoted to the evaluation of different modeling techniques for the prediction of customer churn. Techniques that have been suggested in literature include statistical techniques (e.g., logistic regression (Smith, Willis, & Brooks, 2000), generalized additive models (GAMs) (Coussement, Benoit, & Van den Poel, 2010), survival analysis (Van den Poel & Larivière, 2004)) and classifiers originating from data mining literature (e.g., neural networks (Mozer et al., 2000), support vector machines (Coussement & Van den Poel, 2008a) and decision trees (Smith et al., 2000)).

Nowadays, by utilizing data mining tools for assisting CRM, some techniques, which include decision trees (DT), artificial neural networks (ANN), genetic algorithms (GA), association rules (AR), etc., are usually used in some fields such as engineering, science, finance and business to solve related problems with customers (Witten & Frank, 2005). A decision tree is a flow-chart-like tree structure, where each internal node denotes a test on an attribute, each branch represents an outcome of the test, and leaf nodes represent class or class distributions (Han & Kamber, 2001). An artificial neural network is a large number of highly interconnected processing elements (neurons) that uses a mathematical model, computational model or non-linear statistical data modeling tools for information processing to capture and represent complex input/output relationships. Genetic algorithms, which were formally introduced in the United States in the 1970s by John Holland at University of Michigan, are search algorithms applied to solve problems on a computer based on the mechanics of natural selection and the process of natural evolution (Miller, Todd, & Hegde, 1989). Association Rules based on co occurrence can be used to address relationships that customers which buy X tend to buy Y, and to support related activity of business operations such as product promotions, CRM programs, and inventory control.

Generally, no tool for data mining in CRM is perfect because there are some uncertain drawbacks in it. For example, in decision trees, too many instances lead to large decision trees which may decrease classification accuracy rate and do not clearly create the relationships which come from the training examples. In artificial neural networks, number of hidden neurons, number of hidden layers and training parameters need to be determined, and ANN has long training times in a large dataset especially. Moreover, ANN served as ‘‘black box” which leads to inconsistency of the outputs, is a trial-and-error

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process. In genetic algorithm, GA also has some drawbacks such as slow convergence, a brute computing method, a large computation time and less stability. In association rules, major drawback is the number of generated rules is huge and may be a redundancy.
For solving these problems, two methods, K-means algorithm and RS theory, are worth to be explored, but in this study all the discussions are merely about K-means (Customer value analysis or RFM technique).
K-means is one of the well-known algorithms for cluster analysis and it has been used extensively in various fields including data mining, statistical data analysis and other business applications. Cluster analysis is a statistical technique that are used to identify a set of groups that both minimize within-group variation and maximize between-group variation based on a distance or dissimilarity function, and its aim is to find an optimal set of clusters (Witten & Frank, 2005).

Practical Implications:

Kotler and Armstrong (2006) pointed out that attracting customers is an important task, but retaining customers is more important since losing a customer means losing the entire stream of purchase that the customer would make over a lifetime. Yeh et al. (2009) also stated that the concept of customer relationship management (CRM) is to acquire and retain most profitable customers by understanding their values. When the industry becomes more competitive, it is important for a company to identify and retain high value and important potential customers (Chang et al., 2007; Chiliya et al., 2009; Mutandwa et al., 2009). Moreover, in order to achieve better customer retention and profitability, the company needs to customize marketing strategies and fulfill different customers' needs by allocating resources effectively and efficiently (Huang et al., 2009; Chang et al., 2010). Sohrabi and Khanlari (2007) concluded that since not all customers are equally attractive financially to the company, it is critically important to determine their profitability first and then deploy resources to customers in accordance with their customer values.
As the transaction records of a company become much larger in size, it would be necessary to divide all customers into appropriate number of clusters that are internally homogenous and mutually heterogeneous based on some similarities in these customers from the viewpoint of market segmentation (Hung and Tsai, 2008; Chang et al., 2010). The values of different customer groups can be computed and then evaluated to provide useful decisional information for management. Subsequently, customized marketing strategies can be used to meet different types of customers' needs. Allenby et al. (1998) described that an exact set of segmenting variables for complete market segmentation does not exist. In contrast, Kotler (2003) concluded that customers can be classified by two types of variables including customer characteristics and behavioral variables. Specifically, customer characteristics consist of geographic, demographic and psychographic variables, whereas behavioral variables are composed of attitudes toward the product and the response customers show to the benefit, situation and brand (Wu and Pan, 2009).
RFM (recency, frequency and monetary) model is a behavior-based model used to analyze the behavior of a customer and then make predictions based on the behavior in the database (Hughes, 1996; Yeh et al., 2009).

- The Definition and Scoring pattern of RFM Model

The RFM analytical model is proposed by Hughes (1994), and it is a model that differentiates important customers from large data by three variables (attributes), i.e.
(1) Recency of the last purchase ® which represents recency, which refers to the interval between the time that the latest consuming behavior happens and present. The shorter the interval is, the bigger R is.

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(2) Frequency of the purchases (F) which represents frequency, which refers to the number of transactions in a particular period, for example, two times in a year, two times in a quarter or two times in a month. The bigger the frequency is, the bigger F is.
(3) Monetary value of the purchases (M) which represents monetary, which refers to the monetary value of all transactions in a particular period. The bigger the monetary is, the bigger M is.
According to the literature (Wu & Lin, 2005), researches showed that the bigger the value of R and F is, the more likely the corresponding customers are to produce a new trade with enterprises.
Moreover, the bigger M is, the more likely the corresponding customers are to buy products or services with enterprises again. RFM method is very effective attributes for customer segmentation (Newell, 1997).

The RFM model is the most frequently adopted segmentation technique that comprises three measures (recency, frequency and monetary), which are combined into a three-digit RFM cell code, covering five equal quintile (20% group). Among the three RFM measures, recency is often regarded as the most important one.
However, according to prior findings, RFM values are inclined to be firm-specific and are based on the nature of the products (Lumsden et al., 2008). For example, Fader et al. (2005) found that for lower recency, customers with higher frequency tended to have lower future purchasing potential than those with lower pre-purchasing rates. Lumsden et al. (2008) have similar findings that there are significant differences between groups across recency and frequency.
The process to quantify customer behavior via RFM model is as follows. First, sort the database by each dimension of RFM and then divide the customer list into five equal segments. The method is known to have an exactly equal size. Different RFM quintiles have different response rates. For recency, customers are sorted by purchase dates. Recency is commonly defined by the number of periods since the last purchase, which measures the interval between the most recent transaction time and the analyzing time (days or months), that is, the lower the number of days, the higher the score of recency.
A customer having a high score of recency implies that he or she is more likely to make a repeat purchase. The top 20% segment is coded as 5, while the next 20% segment is coded as 4 and so forth. Finally, the recency for each customer in the database is denoted by a number from 5 to 1 (Hughes, 1996; Kahan, 1998; Tsai and Chiu, 2004).
For frequency, the database is sorted by purchase frequency (the number of purchases) made in a certain time period. The definition of frequency is often simplified to consider two states, including single and repeated purchases. The top quintile is assigned a value of 5 and the others are given the values of 4, 3, 2 and 1. However, higher frequency score indicates greater customer loyalty.
A customer having a high score of frequency implies that he or she has great demand for the product and is more likely to purchase the products repeatedly. For monetary, customers are coded by the total amount of money spent during a specified period of time. The definition of monetary is defined by the dollar value that the customer spent in this time period or by the average dollar amount per purchase or all purchases to date. Marcus (1998) suggested that it is better to use the average purchase amount rather than the total accumulated purchase amount so as to reduce co-linearity of frequency and monetary. Finally, all customers are presented by 555, 554,553, …, 111, which thus creates 125 (5×5×5) RFM cells.
Moreover, the best customer segment is 555, whereas the worst customer segment is 111. Based on the assigned RFM behavior scores, customers can be grouped into different segments and their profitability can be further analyzed (Bult and Wansbeek, 1995; Bitran and Mondschein, 1996; Miglautsch, 2000; Chang et al., 2010). In addition to use the value of each cell to judge whether the customer is valuable, some studies suggest that the possible combinations of RFM can be obtained by assigning _ or _ based on the average R (F, M) value of a cluster being less than or greater than the overall average R (F, M) value. In this case, 8 segments are created. The composite value of RFM is obtained via multiplying normalized

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RFM values of each customer and the weight of RFM variables (Liu and Shih, 2005a, 2005b; Sohrabi and Khanlari, 2007).

Customers were segmented into eight target markets in terms of the period since the last transaction (recency), purchase frequency and total purchase expenditure (monetary). The *k* parameter was set to 8, since eight (2x2x2) possible combinations of inputs (RFM) can be obtained by assigning ↑ or ↓, according to the average to R,F,M values of a cluster being less than or greater than the overall average. If the average R (F, M) value of a cluster exceeded the overall average R (F, M), then an upward arrow ↑ was included, otherwise and downward arrow ↓ was included. For example, R↑F↓M↓ represents that the average recency value of a customer segment is greater than overall average, while frequency and monetary average values are smaller than overall averages. These eight customer groups include best customers (most valuable), valuable customers, shoppers, first-time customers, churn customers, frequent customers, spenders, and uncertain customers (least valuable).
Table **1** presents the result, listing eight clusters, each with their average actual R, F and M values.

cluster	RFM Pattern	Customer Type
C1	R↑F↑M↑	Best
C2	R↑F↓M↑	Valuable
C3	R↑F↑M↓	Shopper
C4	R↑F↓M↓	First Time
C5	R↓F↑M↑	Churn
C6	R↓F↑M↓	Frequent
C7	R↓F↓M↑	Spenders
C8	R↓F↓M↓	Uncertain

Table 1: RFM clusters

The brief explanation of the above mentioned clusters is as follow:

- ***Best Customers:*** It refers to those who bought recently, with a high buying frequency in a definite period of time, with high monetary value in each transaction.
- ***Valuable Customers:*** It refers to those who bought recently, with a low buying frequency in a definite period of time, but with high monetary value in each transaction.
- ***Shopper Customers:*** It refers to those who bought recently, with a high buying frequency in a definite period of time, but with low monetary value in each transaction.
- ***First Time Customers:*** It refers to those who bought recently, but with a low buying frequency in a definite period of time and with low monetary value in each transaction.
- ***Churn Customers:*** It refers to those with a high buying frequency in a definite period of time and high monetary value in each transaction but they haven't bought recently for some specific reasons.
- ***Frequent Customers:*** It refers to those who haven't bought recently and their monetary value of their transaction is not that significant, but they buy frequently in a definite period of time.
- ***Spenders Customers:*** It refers to those who haven't bought recently and they don't buy frequently in a definite period of time but the monetary value of their transactions is very significant.
- ***Uncertain Customers:*** It refers to those who haven't bought recently, with a low buying frequency in a definite period of time and with low monetary value in each transaction. This segment is the most trivial customer cluster with the lowest buying traits.

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In order to fully explain the process of customer segmentation, using RFM technique, the RFM theoretical framework-procedure is presented as follow (figure 1):

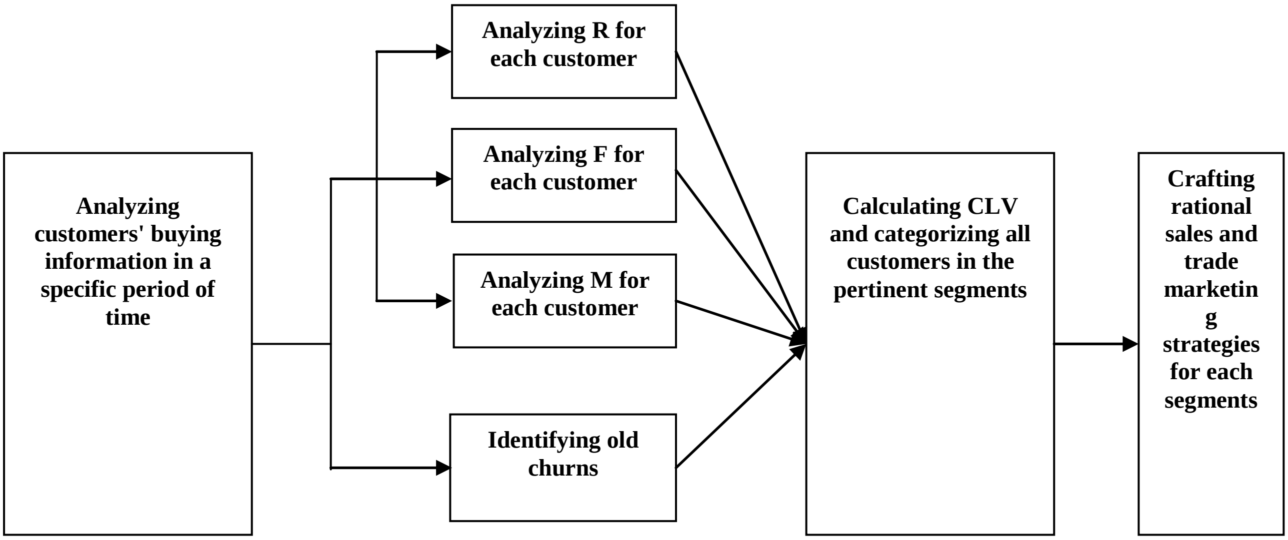

Figure 1 : RFM framework

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- The Application of The RFM Model

The RFM model measures when people buy, how often they buy and how much they buy. While past purchases of customers can effectively predict their future purchase behavior, firms can identify which customer is worthy to be contacted based on his or her past purchase behavior via_RFM model, which is widely applied in database marketing and is a common tool to develop marketing strategies.

Accordingly, RFM models are often developed to target marketing programs (that is, direct mail) for particular customers in order to improve response rates (Sohrabi and Khanlari, 2007), revealing that RFM facilitates to choose which customers to target with an offer (Colombo and Jiang, 1999).

RFM model has been widely applied in many practical areas, including nonprofits and financial organizations (banking and insurance industries) (Hsieh, 2004; Sohrabi and Khanlari, 2007), government agencies (King, 2007), on-line industries (Li et al., 2010), telecommunication industries (Li et al., 2008), travel industries (Ha and Park, 1998; Lumsden et al., 2008) and marketing industries (Spring et al., 1999; Jonker et al., 2006). In addition, RFM model can be used to segment customers, calculate customer value and customer lifetime value (CLV),observe customer behavior, estimate the response probability for each offer type and evaluate on-line reviewers.

One guide line for trade marketing and sales strategies is that the clusters that have RFM values with at least two upper arrow (↑) can be selected as target customers in developing sales and trade marketing campaigns. All customers who belong to these clusters become candidates for conducting suitable marketing strategies, which attract the most attention.

- RFM model weight setup

Kaymak (2001) pointed out that the RFM model is one of the well-known customer value analysis methods. Its advantage is to extract customers' characteristics by using fewer criteria (a three-dimension) which reduce the complexity of the model of customer value analysis (Kaymak, 2001). Moreover, from the consuming behavior point of view, Schijns and Schroder (1996) also deemed that the RFM model is a long-familiar method to measure the strength of customer relationship (Schijns & Schroder, 1996). Retention cost is far less costly than acquisition cost (Kotler, 1994; Peppers & Rogers, 1996); therefore, enterprises are intent via using RFM analysis to mine databases for knowing about customers who spend the most money and create the biggest value for enterprises. Although RFM model is a good method that differentiates important customers from large data by three variables, there are two studies having different opinions with respect to the three variables of RFM model. Hughes (1994) considered that the three variables are equal in the importance (Hughes, 1994); therefore, the weights of the three variables are identical. On the other hand, Stone (1995) indicated that the three variables are different in the importance due to the characteristic of industry (Stone, 1995). Thus, the weights of the three variables are not equal.

One of the most important point in RFM categorization is that in different industries and situation, a different weighting approach should be taken in to account for R,F and M.this approach must be proposed by the sophisticated experts of each field.

- Customer Lifetime Value:

Many firms are now focusing on identifying their most profitable customers and nurturing long-term relations. At the center of the movement is Customer Lifetime Value (CLV), a pivotal concept that pervades many customer relationship management approaches, such as one-to-one, loyalty, and database

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marketing. CLV is the present value of all the future cash flows attributed to a customer relationship (Pfeifer et al., 2005, p. 17).1 Due to uncertainty in future customer, firm, and competitor behaviors, CLV is a random variable and most applications calculate an expected CLV given by:

$$CLV = \sum_{t=1}^{\infty} \frac{E\left[\tilde{V}_t\right]}{(1+d)^{t-1}}$$

Where *V˜t* is the customer's net contribution in period *t*, and *d* is the discount rate. We shall use the term CLV to mean expected lifetime value. The net contribution is determined by: (1) the relationship duration, which is operationalized as the likelihood that the customer still has a relationship with the company in period t; (2) the expected revenues generated by the customer in period t, given he or she is active in that period; and (3) the expected costs of marketing to and serving the customer in period t. There are thus four components of CLV: (1) relationship duration, (2) revenues, (3) costs, and (4) discount rate.

CLV can be used to guide the firm's acquisition and retention activities, and can be aggregated over customers as a measure of firm or segment value. Research on CLV and its components is an active area and there are many research articles that propose methods of estimating CLV or its components under various conditions, study their antecedents, attempt to maximize it over some space of marketing actions, or discuss its applications. Given this widespread interest in customer-relationship centric marketing, it is important to take stock of what is known and needs to be known about CLV.

Our ultimate goal is to produce a set of normative statements such as, if a firm adopts strategies to change some antecedent X, then CLV will increase.

The firm initially performs marketing activities, such as identifying a brand concept, developing a product or service, and orchestrating the marketing mix. This marketing causes affective consumer responses, such as the customer developing attitudes towards the brand/product. Both marketing and affective responses lead to behavioral responses, such as purchase and use of the product. A consumption experience (behavior) can change affect (e.g., a lousy experience could change attitudes, beliefs and satisfaction) and future marketing (e.g., a response to a direct marketing contact usually prompts a series of future contacts). These interactions produce the series of cash flows that determine CLV.

The firm can adopt strategies to change most of the variables listed in the customer relationship box. It can, for example, invest resources in improving the product in hopes of changing satisfaction, advertise to change attitudes and beliefs, use promotions to encourage multi-channel purchasing or cross-buying, etc. The question we would like to answer is whether such investments affect CLV. We have identified four findings that we believe qualify as empirical generalizations regarding CLV: customer satisfaction, marketing, cross-buying, and multichannel purchasing all have positive relationships with CLV.

Firms must formulate marketing activities to manage CLV over time. Note however that most of the evidence is based on associations, the problem is that firms might choose to
spend higher marketing efforts on more valuable customers, and thus CLV caused increased marketing rather than the reverse. A formal selectivity model (Woodridge, 2002) would be needed to sort out the causality issue, where there would be two equations: one for customer profitability and the second for firm marketing efforts (Reinartz et al., 2005).

Reinartz and Kumar (2003, pp. 81–82) give a literature review and develop a theoretical rational for cross-buying having a positive effect on duration, There is generally a positive effect, directly on CLV components such as lifetime duration and revenues, but also through an association with aggregate measures related to CLV such as firm performance, although some authors do not find a significant effect. There is some question as to whether the relationship between cross-buying and CLV is spurious.

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It could be that customers who highly prefer a company buy often from it and also buy from several departments. For example, if customers are loyal to a given electronics retailer because of its service, they are likely to make multiple purchases from that retailer such as TV's, DVD's, and computer equipment. Reinartz, Thomas, and Bascoul (2008) used Granger causality tests to assess the direction of causality, and found that profitability caused cross-buying rather than the reverse. So while we clearly have a
Multichannel purchasing is associated with higher CLV: This is a significant finding in the multichannel literature (see Neslin and Shankar, 2009; Neslin et al., 2006). It occurs mostly through an association with revenues — the multichannel customer generates more revenues. Furthermore, the addition of the Internet channel improves customer retention and CLV (Boehm, 2008). Multichannel purchasing could create switching costs or increases in customer satisfaction.
For example, customers who use a bank's ATM, branch office, and online service, must extricate themselves from several contact points in order to switch to another bank.
Hence switching costs are high. In a more positive vein, customers may be more satisfied because dealing with the bank is convenient and they therefore give it more business.
The evidence in favor of a positive association is fairly strong, especially, although not exclusively, in the retail industry. One interesting exception can be found in Campbell and Frei (2006), who find that while adopters of online banking increase usage frequency, total revenue goes down, possibly due to customers managing their assets more effectively.
The question of causality rears its head again in the case of multichannel usage. Conceptually, the situation is similar to the cross-buying case — multichannel purchasing is “crossbuying” across the firm's channels rather than the firm's
departments. Again, the multichannel shopper may become more satisfied with the company, and hence becomes more loyal and more valuable. The shopper may also receive more marketing simply by visiting various channels. On the other hand, high-value customers may self-select into using all the firm's channels. This explanation is refuted by Ansari et al. (2008), but that is only one study. Further work is needed in this area. If indeed the relationship is multichannel and increases CLV, the implication is clear — firms should encourage multichannel usage.4

How are RFM related to CLV?

Previous purchase behavior is often summarized by RFM: the time since the most recent purchase (R=recency), the number of previous purchases (F=frequency), and the total amount spent (M=monetary value). Since these variables are widely known for existing customers, they are often included in CLV models and used to make customer-level estimates.
Frequency and monetary value are often highly correlated and it could be argued that, at least in some situations, they are different measures of the same underlying construct, previous buying intensity. One way to combine them is to take calculate average spend per transaction, equal to M/F.
In our discussions with practitioners, most believe that recency has a negative relationship with CLV (the longer a customer has been inactive the lower CLV is), and frequency and monetary have a positive relationship with CLV. Reinartz and Kumar (2003) find positive relationships between previous spending levels and lifetime duration. Donkers et al. (2007) find that those who have purchased insurance recently are more likely to buy again in the future.
RFM analysis is based on the marketing principle that “80% of your business comes from 20% of your customers” and is a very effective way to start to develop more productive and profitable sales and marketing strategies!

80% of your business comes from 20% of your customers

In the boardrooms of many retailers, the question is often asked: How do we increase our sales? It is found that across a wide range of retailers, many don't know or even use the well-known segmentation

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model called RFM. Some may only use one indicator or maybe two. And when they do use RFM (Recency, Frequency and Monetary value), they don't typically do so effectively.

The most powerful determinant of whether your customer will buy again is how recently (R - weighted 35%) they made their previous purchase. Response rates rapidly decline as the buyer 'aged.' Frequency (F - weighted 50%) is the second most powerful indicator of response. Buyers who have made large purchases (M - weighted 15%) are more likely to continue to spend at higher levels.

When one combines all three segmentation indicators, your response rates and conversion to sales will increase dramatically. In addition to these, other important indicators to take into consideration are what they have bought (knowing the types of products your customers purchase or services they use, will allow you to predict their lifestyle and will assist with cross- and up-sell opportunities). Adding in gender, age and other relevant demo- and geographic's will again enhance your response and conversion rates. However, what is important is that you use only the two or three additional criteria that would positively influence your results.

In most cases the profit from your customers doesn't come from their first purchase, but from buying continuously from you over a number of years. That is what you should be interested in - their lifetime value. ROI is normally calculated on the Lifetime Value (LTV) of your customer - your total earnings from them over their lifetime with you. As part of your long-term business strategy, you need to calculate what this number is before you embark on any marketing campaigns.

Lifetime Value is measured on Recency, Frequency, Monetary value and product category. Use the RFMP indicators to decide which of your customers you should market to, when, how often and what products and services to offer. Don't waste your marketing investment on those customers who are less likely to buy again.

Responsible businesses think of marketing and trade marketing as an investment and not as expenditure. Many businesses often fail because their marketing approach is a cost centre rather than a profit centre point of view.

ROI driven marketing can enhance customer retention, prevent defections and churn, and allow you to identify and sell more to those customers who are predisposed towards your company's products or services and brand - but who are currently spending only a small amount of their available budget with you.

A ROI focus can also assist you to reduce operating expenses, by identifying those activities that add no value and that can be safely scaled back or abandoned altogether. You can also use it to improve staff productivity by communicating your business and marketing objectives to them and give regular feedback on program results.

A clear, consistent focus on your customer will always generate more and regular business, as relationship building and loyalty naturally stem from asking your customers what they want and doing whatever it takes to meet their stated needs.

The reality is that most businesses make little attempt to segment their customers based on value. As a result, you may be putting your highly profitable customers at risk while wasting money on your low valuable customers.

Customer profitability cannot be viewed in a vacuum. Performance measures for market share, customer acquisition, retention and satisfaction (commitment as it is called now), must be identified, calculated and factored into the planning, implementation and evaluation of your full marketing program.

In today's challenging economic environment, you need to know the real costs and actual revenue generated for each element of your marketing investment. With this business intelligence in hand you can plan and invest more effectively in the future.

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It seems apparent that in these days of rising costs on all fronts - the need is more and more for profit-producing, accountable marketing techniques and effective controlled marketing investment is more necessary than ever before.

Conclusion:

This study proposes a novel three-step approach which uses RFM analysis to classify all customers into rational-distinct categories (Best, Valuable, Shopper, Firsts, Spenders, Churns, Frequent, Uncertain). For sales and trade marketing managers, our overview of the literature provides useful insights on how to execute RFM in their daily practices. Although the academic literature has developed useful methods for targeting the right customers with the right offer at the right time and for predicting future behavior and customer value, the nature of FMCG industry and multi-dimensional approach in RFM lead the researcher to highlight the significance of customer analysis based on the RFM technique. Moreover this knowledge can be used to improve sales, trade marketing and marketing decision-making in the increasingly competitive retail environment.

References:

Allenby GM, Arora N, Ginter JL (1998). On the heterogeneity of demand. J. Mark. Res., 35: 384-389.

Blattberg, R. C., Kim, B.-D., & Neslin, S. A. (2008). Database marketing: Analyzing and managing customers. New York: Springer.

Boehm Martin (2008), "Determining the Impact of Internet Channel Use on Customer's Lifetime," Journal of Interactive Marketing, 22 (3), 2–22.

Campbell Dennis and Frances X. Frei (2006), The Cost Structure, Customer Profitability, and Retention Implications of Self-Service Distribution Channels: Evidence from Customer Behavior in an Online Banking Channel. Working Paper. Cambridge, MA: Harvard Business School.

Chan, Chu-Chai Henry (2005). Online auction customer segmentation using a neural network model. International Journal of Applied Science and Engineering, 3(2), 101–109. Chang EC, Huang SC, Wu HH (2010). Using K-means method and spectral clustering technique in an outfitter's value analysis. Qual Quant., 44(4): 807-815.

Chang EC, Huang SC, Wu HH, Lo CF (2007). A case study of applying spectral clustering technique in the value analysis of an outfitter's customer database. 2007 IEEE Inter. Confer. Ind. Eng. Eng. Manage., 1743-1746.

Chiliya N, Herbst G, Roberts-Lombard M. 2009. The impact of marketing strategies on profitability of small grocery shops in South African townships. Afr. J. Bus. Manage., 3 (3): 70-79.

Colombo R, Jiang W (1999). A stochastic RFM model. J. Interact. Mark., 13(3): 2-12.

Cooil, B., Keiningham, T. L., Aksoy, L., & Hsu, M. (2007). A longitudinal analysis of customer satisfaction and share of wallet: Investigating the moderating effect of customer characteristics. Journal of Marketing, 71(1), 67–83.

Coussement, K., & Van den Poel, D. (2008a). Churn prediction in subscription services: An application of support vector machines while comparing two parameter-selection techniques. Expert Systems with Applications, 34(1), 313–327.

Coussement, K., Benoit, D. F., & Van den Poel, D. (2010). Improved marketing decision making in a customer churn prediction context using generalized additive models. Expert Systems with Applications, 37(3), 2132–2143.

DOI: 10.9756/IAJAFM/V6I1/1910009

Received:15 February 2019/Accepted:6 May 2019/Published:13 June 2019

Fader PS, Hardie BGS, Lee KL (2005). RFM and CLV: Using Iso-Value curves for customer base analysis. J. Mark. Res. 415-430.

Fraley, Andrew, & Thearting, Kurt (1999). Increasing customer value by integrating data mining and campaign management software. Data Management,

Gupta, S., Lehmann, D. R., & Stuart, J. A. (2004). Valuing customers. Journal of Marketing Research, 41(1), 7–18.

Ha SH, Park SC (1998). Application of data mining tools to hotel data mart on the Intranet for database marketing. Expert Syst. Appl., 15(1): 1-31.

Han, J., & Kamber, M. (2001). Data mining: Concepts and techniques. San Francisco: Morgan Kaufmann Publishers.

Hsieh NC (2004). An integrated data mining and behavioral acoring model for analyzing bank customers. Expert Syt Appl., 27: 623-633.

Huang SC, Chang EC, Wu HH (2009). A case study of applying data mining techniques in an outfitter's customer value analysis. Expert Syst. Appl., 36: 5909-5915.

Hughes, A. M. (1994). Strategic database marketing. Chicago: Probus Publishing Company.

Hung C, Tsai C (2008). Market segmentation based on hierarchical self-organizing map for markets of multimedia on demand. Expert Syst. Appl., 34(1): 780-787.

Jones, Joni L., Easley, Robert F., & Koehler, Gary J. (2006). Market segmentation within consolidated E-markets: A generalized combinatorial auction approach. Journal of Management Information Systems, 23(1), 161–182.49–53.

Jonker, Jedid-Jah, Piersma, Nanda, & Poel, Dirk Van den (2004). Joint optimization of customer segmentation and marketing policy to maximize long-term profitability. Expert Systems with Applications, 27, 159–168.

Kahan R (1998). Using database marketing techniques to enhance your one-to-one marketing initiatives. J. Consum. Mark., 15(5): 491-493.

Kaymak, U. (2001). Fuzzy target selection using RFM variables. In IFSA World congress and 20th NAFIPS international conference, Vol. 2 (pp. 1038– 1043).

Kim, Yong Seog, & Street, W. Nick (2004). An intelligent system for customer targeting: A data mining approach. Decision Support Systems, 37, 215–228.

Kim, Yong Seog, Street, W. Nick, Russell, Gary J., & Menczer, Filippo (2005). Customer Targeting: A Neural Network Approach Guided by Genetic Algorithms. Management Science, 51(2), 264–276.

King SF (2007). Citiznes as customers: Exploring the future of CRM in UK local government. Gov. Inform Q., 24: 47-63.

Kolter P (2003). Marketing Management, Eleventh Edition, Pearson Education, New Jersey.

Kotler P, Armstrong G (2006), Principles of Marketing, Eleventh Edition, Pearson Prentice Hall, New Jersey.

Kotler, P. (1994). Marketing management: Analysis, planning, implementation, and control. New Jersey: Prentice-Hall.

Kuo, R. J., An, Y. L., Wang, H. S., & Chung, W. J. (2006). Integration of self-organizing feature maps neural net work and genetic K-means algorithm for market segmentation. Expert Systems with Applications, 30, 313–324.

Larivière, B., & Van den Poel, D. (2005). Predicting customer retention and profitability by using random forests and regression forests techniques. Expert Systems with Applications, 29(2), 472–484.

Liu DR, Shih YY (2005a). Integrating AHP and data mining for product recommendation based on customer lifetime value. Inform. Manage., 42: 387-400.

Liu DR, Shih YY (2005b). Hybrid approaches to product recommendation based on customer lifetime value and purchase preferences. J. Syst. Softw., 77: 181-191.

DOI: 10.9756/IAJAFM/V6I1/1910009

Received:15 February 2019/Accepted:6 May 2019/Published:13 June 2019

Lumsden SA, Beldona S, Morison AM (2008). Customer value in an all-inclusive travel vacation club:An application of the RFM framework. J. Hosp. Leisure Mark., 16(3): 270-285.

Miller, G. F., Todd, P. M., & Hegde, S. U. (1989). Designing neural networks using genetic algorithms. In J. D. Schaffer (Ed.), Proceedings of the 3rd international conference on genetic algorithms (pp. 379 384). San Mateo, CA: Morgan Kaufmann.

Mozer, M. C., Wolniewicz, R., Grimes, D. B., Johnson, E., & Kaushansky, H. (2000). Predicting subscriber dissatisfaction and improving retention in the wireless telecommunications industry. IEEE Transactions on Neural Networks, 11(3), 690–696.

Mutandwa E, Kanuma NT, Rusatira E, Kwiringirimana T, Mugenzi P, Govere I, Foti R (2009). Analysis of coffee export marketing in Rwanda: Application of the Boston consulting group matrix. Afr. J. Bus. Manage., 2(4): 210-219.

Neslin Scott A. and Venkatesh Shankar (2009), "Key Issues in Multichannel Customer Management: Current Knowledge and Future Directions," Journal of Interactive Marketing, 23 (1), 70–81.

Neslin Scott A. (2002), Sales Promotion, Relevant Marketing Series. Cambridge, MA: Marketing Science Institute.

Neslin, S. A., Gupta, S., Kamakura, W., Lu, J. X., & Mason, C. H. (2006). Defection detection: Measuring and understanding the predictive accuracy of customer churn models. Journal of Marketing Research, 43(2), 204–211.

Newell, F. (1997). The new rules of marketing: How to use one-to-one relationship marketing to be the leader in your industry. New York: McGraw-Hills Companies Inc.

Peppers, D., & Rogers, M. (1996). The one to one future: Building relationships one customer at a time. NY: Doubleday.

Pfeifer Philip E. and Heejung Bang (2005), "Non-arametric Estimation of Mean Customer Lifetime Value," Journal of Interactive Marketing, 19 (4), 48–66.

Reinartz Werner J. and V. Kumar (2000), "On the Profitability of Long-Life Customers in a Noncontractural Setting: An Empirical Investigation and Implications for Marketing," Journal of Marketing, (), 17–35.

Reinartz Werner J., Jacquelyn S. Thomas, and V. Kumar (2005), "Balancing Acquisition and Retention Resources to Maximize Customer Profitability," Journal of Marketing, 69 (January), 63–79.

Reinartz, W., & Kumar, V. (2002). The mismanagement of customer loyalty. Harvard Business Review, 80(7), 86–94.

Rust, R. T., & Zahorik, A. J. (1993). Customer satisfaction, customer retention, and market share. Journal of Retailing, 69(2), 193–215.

Schijns, J. M. C., & Schroder, G. J. (1996). Segment selection by relationship strength. Journal of Direct Marketing, 10, 69–79.

Shin, H. W., & Sohn, S. Y. (2004). Segmentation of stock trading customers according to potential value. Expert Systems with Applications, 27, 27–33.

Smith, K. A., Willis, R. J., & Brooks, M. (2000). An analysis of customer retention and insurance claim patterns using data mining: A case study. Journal of the Operational Research Society, 51(5), 532–541.

Sohrabi B, Khanlari A (2007). Customer lifetime value (CLV) measurement based on RFM model. Iranian Acc. Aud. Rev., 14(47): 7 20.

Spring P, Leeflang PSH, Wansbeek T (1999). The combination strategy to ptimal target selection and offer segmentation in direct mail. J. Mark. Focused Manage., 4: 187-203.

Stone, B. (1995). Successful direct marketing methods. Lincolnwood, IL: NTC Business Books. pp. 37 57.

Tsai CY, Chiu CC (2004). A purchase-based market segmentation methololology. Expert Syst. Appl., 27: 265-276.

DOI: 10.9756/IAJAFM/V6I1/1910009

Received:15 February 2019/Accepted:6 May 2019/Published:13 June 2019

Van den Poel, D., & Larivière, B. (2004). Customer attrition analysis for financial services using proportional hazard models. European Journal of Operational Research, 157(1), 196–217.

Wedel, M., & Kamakura, W. A. (2000). Market segmentation: Conceptual and methodological foundations (2nd ed.). Dordrecht: Kluwer.

Witten, I. H., & Frank, E. (2005). Data mining: Practical machine learning tools and techniques (2nd ed.). USA: Morgan Kaufmann Publishers.

Woo, Ji Young, Bae, Sung Min, & Park, Sang Chan (2005). Visualization method for customer targeting using customer map. Expert Systems with Applications, 28, 763–772.

Woodridge Jeffrey M. (2002), Econometric Analysis of Cross Section and Panel Data. Cambridge, MA: The MIT Press.

Wu HH, Pan WR (2009). An integrated approach of Kano model and ANOVA technique in market segmentation – a case of a coach company. J. Stat. Manage. Syst., 12(4): 679-691.

Wu, J., & Lin, Z. (2005). Research on customer segmentation model by clustering. ACM International Conference Proceeding Series, 113.

Xie, Y. Y., Li, X., Ngai, E. W. T., & Ying, W. Y. (2009). Customer churn prediction using improved balanced random forests. Expert Systems with Applications, 36(3), 5445–5449.

Yeh IC, Yang KJ, Ting TM (2008). Knowledge discovery on RFM model using Bernoulli sequence. Expert Syst. Appl., 36: 5866 5871.

DOI: 10.9756/IAJAFM/V6I1/1910009

Received:15 February 2019/Accepted:6 May 2019/Published:13 June 2019