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Review

A review of the application of RFM model

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RFM (Recency, Frequency and Monetary) model has been widely applied in many practical areas in a long history, particularly in direct marketing. By adopting RFM model, decision makers can effectively identify valuable customers and then develop effective marketing strategy. This paper aims to provide a comprehensive review on the application of RFM model. In addition, this paper depicts the definition and the scoring scheme of RFM and summarizes how RFM model has been effectively applied in a wide variety of areas. Furthermore, this paper presents the advantages and disadvantages of the RFM model. The relative advantages and disadvantages of RFM and other models are also exploited. Finally, this paper describes the extended RFM model via a presentation of how RFM combines with other variables and models.

Key words: RFM model, literature review, customers, direct marketing, customer value, customer relationship management.

INTRODUCTION

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

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behavior in the database (Hughes, 1996; Yeh et al., 2009). Moreover, recency represents the length of a time period since the last purchase, while frequency denotes the number of purchase within a specified time period and monetary means the amount of money spent in this specified time period (Wang, 2010). In fact, these three variables belong to the behavioral variables and can be used as the segmenting variables by observing customers' attitudes toward the product, brand, benefit, or even loyalty from the database.

Consequently, this paper needs particular depictions to answer the following issues.

(i) What are the definitions and scoring schemes of the RFM model?
(ii) How is the RFM model applied?
(iii) What are the advantages and disadvantages of the RFM model?
(iv) What are the relative advantages and disadvantages of the RFM model and other models?
(v) How is the RFM combined with other variables or other models?

THE DEFINITION AND SCORING SCHEME OF THE RFM MODEL

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 segments and their profitability can be further analyzed (Bult and Wansbeek, 1995; Bitran and Mondschein, 1996; Miglautsch, 2000; Chang et al., 2010).

In the study of Miglautsch (2000), the RFM scoring method is called customer quintile method. The customer quintile method is to sort customers in descending order (from the best to the worst). The advantage is to yield equal number of customers in each segment. However, this method has a major disadvantage. It encounters several scoring challenges in the measure of frequency and is relatively sensitive, which leads to pulling apart customers who have identical behavior at the lower quintiles, but group customers together whose buying behaviors have significant differences (Alam and Khalifa, 2009).

There is another scoring method (behavior quintile scoring method) developed by John Wirth (The founder of Woodworker's Supply of New Mexico), which sorts customers based on their behavior and thus may have different number of customers in each quintile. The scoring scheme of frequency covers five intervals, including 0 to 3 months, 4 to 6 months, 7 to 12 months, 13 to 24 months and 25+ months, which are coded as 5, 4, 3, 2 and 1, respectively. This method is known as hard coding (McCarty and Hastak, 2007). For frequency, although this scoring method appears to solve the sensitivity problems, it still encounters similar problems as customer quintile method in the frequency measure. Hence, Miglautsch (2000) proposed to combine behavior quintile scoring method and the mean scoring method developed by Ted Miglautsch (V. P. Development, Miglautsch Marketing, Inc.). The score of frequency is defined with regards to the fact that the single purchasers are assigned a score of 1. Then, the average of the remaining frequency values is used to determine the mean. Once a customer's total frequency value is lower than the mean, a score of 2 is given to this customer. The process may be repeated more than two times. For monetary, five quintiles are still created and each has equal amounts of sales.

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

When discussing the weighting scheme of RFM model, there are two ways to create a single RFM value. One method, proposed by Libey is to add the values of recency, frequency and monetary together by adding the average order and frequency per year, while the other method is more commonly applied in practice by adding together the RFM scores (Miglautsch, 2000). According to Hughes (1994), each measure of RFM has the same weight when calculating a composite score. For instance, for the cell (5, 2, 4), the composite score is 11 (5+2+4). However, Miglautsch (2000) indicated that there is also a possibility that different weight is given to each measure of RFM. Moreover, a formula of summing the RFM score is given as total composite score = (R×3) + (F×2) + (M×1) (Miglautsch, 2000). Furthermore, Miglautsch (2000) stated that there is another formula to compute a composite score, that is, total composite score = (R×9.9) + (F×6.6) + (M×3.3). In contrast to the formulas depicted by Miglautsch (2000), Tsai and Chiu (2004) pointed out that the sum of the weight of each RFM measure should be equal to 1. Stone (1995), on the other hand, assigned different weights to RFM measures for computing a single RFM value when the characteristics of the product and industry are taken into account. Specifically, the latest purchase is assigned as a weight of 24 if it is within 3 months, 12 if it is between 3 and 6 months, 6 if it is between 6 and 9 months, 3 if it is between 9 and 12 months and 0 if it is longer than 12 months for evaluating recency value. The weighted value of frequency is computed via multiplying the purchasing frequency with 4 points, while that of monetary is computed via multiplying the purchasing amount with 10% (the highest value is 9).

Rather than arbitrarily assigning a particular weight to each RFM variable, Liu and Shih (2005a, 2005b) applied analytic hierarchy process to determine the relative weights of RFM variables. McCarty and Hastak (2007), on the other hand, assigned a weight to each of the RFM measure based on past experience and then created a function of the judgment of the database marketers with a particular database, which is referred to as judgment-based RFM. Unlike judgment-based RFM, Hughes (1994) proposed empirically-based RFM method with two steps. The first step is similar to the customer quintile method, while the second step is to conduct a test mailing to a randomly sampled subset of each cell (that is, 10%). When getting the responses of the test mailing, the proportion of respondents in each cell can be obtained. Next, the cells can be ordered as a function of response percentage. The marketer can then either select to mail to a particular part of the remaining file (that is the top 20% of the cells) or select to mail to the cells which are above a break of the percentage, which divides mailing costs by the revenue received per order. This leads the importance of each RFM measure to be determined by the test mailing for the particular offer.

Tsai and Chiu (2004) summarized that a single RFM value via actual scores retrieved from the original transaction database can be further transformed into a z-score rather than coding each value of RFM measures into a particular score. After the transformation of the RFM scores, a single RFM value is created by multiplying each RFM value and the weight.

The definition of the RFM model previously mentioned has some minor modification based on the focus of the study. For instance, Hsieh (2004) examined banking customers' behavior by considering recency measures as the average time distance between the day of making a charge and the day of paying the bill. Frequency measures the average number of credit card purchase made, and monetary measures the amount of consumption spent during a yearly time period. Li et al. (2008) defined recency as the most recent traffic time that lasts for 3 hours and its network flow exceeds the threshold. Frequency is defined as the usage counts over 7 weeks, with each usage lasting for 3 hours and its network flow exceeding the threshold. Monetary is defined as the cost per network traffic unit, which is calculated as network-monthly-rental/monthly-network-traffic. However, Lumsden et al. (2008) examined private travel vacation club in America. They defined recency as a variable that seeks to know the year in which the member bought the most recent vacation. Frequency is defined as the number of vacations via the number of years spent in the club, whereas monetary is defined as the average spending per vacation. On the contrary, Chan (2005) examined online auction customers by defining recency as the total bid period, frequency as the total number of bids and monetary as the final bid price.

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).

Firms can get much benefit from the adoption of RFM, encompassing increased response rates, lowered order cost and greater profit. In the application of RFM model, each customer's name and address needs to be assigned by a unique key (that is, an account number) and order, and the sales information needs to be stored with the unique key included in each transaction record (Hughes, 1996; Kahan, 1998). The analysis of RFM is to examine customer transaction history, including an observation of the purchasing time, purchasing frequency and purchasing monetary amount, and thus to help identify significant and valuable customers (Miglautsch, 2000, 2002). Customers can be classified into different types of groups via RFM. Thompson (2002) applied RFM model to classify customers into uncertain customers, spenders, frequent customers and the best customers.

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.

Several studies employ the RFM model to calculate CLV (Liu and Shih 2005a; Sohrabi and Khanlari, 2007). Liu and Shih (2005a) developed a novel product recommendation methodology that combined group decision-making and data mining techniques by utilizing AHP, clustering and association rule mining techniques. Besides, they applied RFM to evaluate CLV. Four methods were compared in their study, namely weighted-RFM method, non-weighted RFM method, the non-clustering method and the typical collaborative filtering (CF) method. Weighted-RFM method considers the relative importance of the RFM variables via AHP, while the non-weighted RFM method does not. The non-clustering method makes an association rule-based recommendation before clustering. The CF method utilizes preference ratings given by various customers to determine recommendations to a specific customer according to the opinions of other customers. The findings showed that the proposed methodology can yield better recommendations in terms of higher quality. Sohrabi and Khanlari (2007) used K-means clustering technique to develop a CLV model by determining customers' CLV and segmentation by taking into account the RFM measures.

RFM model has also been widely used to identify customers and analyze customer profitability. For instance, Kaymak (2001) used RFM variables as features for characterizing the customers when examining how fuzzy clustering can be used to obtain target selection models. The methods for target selection include segmentation methods and scoring methods. In order to improve unreliable segmentation result due to the traditional adoption of general variables such as customer demographics and lifestyle to segment a market, Tsai and Chiu (2004) introduced a novel purchased-based market segmentation methodology in accordance with product specific variables (that is, the purchased items and associated monetary expenses from transactional customer histories). After segmentation, they used a designated RFM model to analyze the relative profitability for each customer cluster, which helps provide more marketing opportunities and aid marketers to revise their marketing strategies (Sohrabi and Khanlari, 2007).

Jonker et al. (2006) provided a decision support system to determine mailing frequency for active customers such that direct mailers with tools can define the preferred response behavior and provide advices on the mailing strategy that can motivate customers towards this preferred response behavior. The system observes the mailing pattern of customers in terms of RFM variables and provides mailing policies for multiple time periods. As such, the mailing decision process is modeled through a Markov decision chain.

Lumsden et al. (2008) applied the RFM model to distinguish customer value according to pre-purchase motivations of membership initiation in all-inclusive travel vacation club. Chan (2008) proposed an approach that combines customer targeting and customer segmentation for campaign strategies using RFM to identify customer behavior and a CLV model to evaluate the proposed segmented customers via examining Nissan automobile retailer. The findings showed that the proposed method produces better results in targeting valuable customers than random selection.

Similarly, Spring et al. (1999) proposed a combination strategy of target selection and the selection of the strongest offer via a response model which makes target selection specific to direct mail offer. A logit model is deployed with standard RFM variables to estimate the response probability for each offer type. The findings showed that the combination strategy can achieve greater profits. Colombo and Jiang (1999) also presented a simple stochastic RFM model to target customers in the firm's database by only considering recency and frequency to predict response probability and predicting an expected contribution with the combination of the response probability and monetary value.

Hsieh (2004) proposed an integrated data mining and behavioral scoring model to manage existing credit card customers in a bank by a self-organizing maps neural network to predict profitable groups of customers based on repayment behavior and RFM behavioral scoring predictors.

The results reveal that the values of RFM and repayment behavior are behavioral scoring predictors affecting customer segmentation. Therefore, the groups of customers were profiled through customers' feature attributes such as age and credit card usage and the customer credit card marketing strategies were developed for different groups of customers (Alam, 2009).

Chan (2005) focused on e-auction market by using self-organizing maps to segment online auction customers into homogeneous groups, and as such, the online bidder behaviors can be understood by observing the RFM variables.

In contrast to e-auction market, Li et al. (2008) proposed a 'business intelligence' process for ISP dealers of the telecommunication industry in Taiwan. Self-organizing maps were applied to divide customers into clusters with different usage behavior patterns, and the RFM model was performed to calibrate customers' value of each cluster to help the management develop effective marketing strategies (Ha and Park, 1998).

Cheng and Chen (2009) developed a procedure that joins RFM attributes and K-means algorithm into rough sets theory so as to enhance classification accuracy and extract classification rules for achieving an excellent CRM for enterprises. Hence, they applied RFM to understand customer consuming behavior to segment different groups of customers. Ha and Park (1998) applied data mining tools to increase the amount of sales of the target duty-free shop based on RFM data extracted from the customer information of the data mart through the enterprise intranet.

The RFM model can not only be applied to analyze customer behaviour, but can also be used to analyze the behavior of on-line reviewers. Li et al. (2010) combined RFM and a modified pointwise mutual information (PMI) measures to calculate the influential power of real online users through their reviews. At the beginning, they analyzed the comments written by each reviewer through text-mining techniques, which were quantified by a modified PMI measure.

At the same time, they measured the RFM scores of the reviewers by quantifying the reviewing recency and frequency of the authors. Later, they combined the PMI- and RFM-based scores so that they can determine, whether a reviewer has the infective ability or is valuable in the word-of-mouth marketing, which is an action for informally sharing experiences and spreading information among consumers based on their safisfaction with particular products (Mangold et al., 1999). The findings showed that the proposed model can accurately identify which reviewers should be chosen to become the influential nodes.

THE ADVANTAGES AND DISADVANTAGES OF THE RFM MODEL

There are several reasons why the RFM model is popular in direct marketing segmentation for decades. First, RFM is cost-effective in acquiring important customer behavior analysis and is easy to quantify customer behavior (Kahan, 1998; Miglautsch, 2000), where customers and transactional data can be stored in an accessible electronic form (Lumsden et al., 2008). As such, decision makers can easily understand the application of RFM model (McCarty and Hastak, 2007; Wang, 2010). Secondly, RFM is very valuable in predicting response and can boost a company's profits in a short term (Baecke and Van den Poel, 2009). Thirdly, it is very effective to model with RFM variables as the purchase behavior can be summarized by using a very small number of variables. Fourthly, RFM variables are gathered via an internal database containing customer-specific information regarding the transaction history and are not obtained through the aggregate level information in the demographic databases. Hence, RFM is more meaningful for targeting particular customers (Kaymak, 2001). Fifthly, RFM is a long-familiar method to measure the strength of customer relationship as RFM can effectively identify valuable customers (Wang, 2010).

Although RFM model is a crucial tool for firms to develop marketing strategies, it also has several disadvantages. First, given that RFM aims to identify valuable customers in firms, it only focuses on the best customers. It provides little meaningful scoring on recency, frequency and monetary when most customers do not buy often, spent little and have not purchased lately. This is particularly true for most of the firms' sales, 80% of which come from 20% of the customers (Hughes, 1996; Wang, 2010) (80 to 20 rule). Accordingly, it ignores the analysis on new firms setting up in a short period and customers that only purchase once and placed small orders. Miglautsch (2002) referred to this type of customers as 1-1-1 customers and asserted that they are the biggest customers segment and may have the greatest untapped potential.

Secondly, RFM model can only use limited number of selection variables. However, most household characteristics have effect on the probability of customer response. The simplicity of RFM model has been overemphasized and its ability to differentiate has little to be considered. Previous literature has indicated that it is better to take relational information into account when using RFM models (McCarty and Hastak, 2007). Thirdly, unless RFM-variables are all mutually independent, RFM model does not double count (Bult and Wansbeek, 1995; Chan, 2005; Baecke and Van den Poel, 2009). Fourthly, RFM focuses on a company's current customers and cannot be applied to the prospecting for new customers as a marketer does not have transactions for prospects (McCarty and Hastak, 2007). Fifthly, RFM estimates a single response model for all customers in the database and thus assumes the homogeneous customer database, which is often contrary to the real situation that customers often have a considerable heterogeneity (Suh et al., 1999). Sixth, RFM is not predicted as a precise quantitative model and the importance of each RFM measure is different among industries (Yeh et al., 2009).

In summary, RFM model has weaknesses in some areas that lead to some resolutions on the disadvantages of RFM model or some minor modification or extension on RFM model. For instance, Miglautsch (2002) suggested that sub-segmentation can help identify 1-1-1 customers, involving three classes of variables: internal purchase information, geo-demographic information connected to postal code and customer variables.

THE RELATIVE ADVANTAGES AND DISADVANTAGES OF RFM AND OTHER MODELS

New models have been incorporated into the RFM model to increase predictability. For example, Liu and Shih (2005b) proposed two hybrid methods that exploit the advantage of a weighted RFM-based method (WRFM-based method) or the preference-based Collaborative Filtering (CF) method in improving the quality of recommendations of products. Their findings indicated that the propsed hybrid methods are superior to the other two methods.

Rust and Verhoef (2005) provided a fully personalized model for optimizing multiple marketing interventions in intermediate-term (CRM) by conducting a longitudinal validation test to compare the performance of the model with that of the commonly used segmentaiton models in predicting the intermediate-term and customer- specific gross profit change, including demographic model, RFM model and finite mixture models. Their results show that the proposed model outperfomed traditional segmentation models in predicting the effectivnesss of the intermediate-term (CRM).

McCarty and Hastak (2007) examined different approaches for direct marketing segmentation, namely RFM, Chisquare Automatic Interaction Detection (CHAID) and logistic regression. Their findings concluded that CHAID outperforms RFM in the situation that the response rate to mailing is low and the mailing would be limited to a very small portion of the database. However, RFM is an acceptable technique in other situations.

Wang (2010) adopted a hybrid method that incorporates kernel induced fuzzy clustering techniques to detect outliers efficiently and to segment customers more effectively, including robust possibilistic clustering method and robust fuzzy clustering method by using two real dataset, regarding the WINE dataset and the RFM dataset to validate the hybrid method. The results revealed that the proposed method can fulfill both robust classification and robust segmentation in the application of the noisy dataset.

COMBINING RFM WITH OTHER VARIABLES OR OTHER MODELS

Given the weakness of RFM models, some papers have attempted to improve the predictability of RFM models via adding more additional variables to predict customer behavior or develop new models to test whether they perform better than RFM. For instance, Buckinx and Poel (2005) built a model to predict partial defection by behaviorally loyal clients adopting three classification techniques: Logistic regression, Automatic Relevance Determination (ARD) neural networks and random forests in a non-contractual setting and obtained data from an FMCG retailer. They used the observed past purchase behavior variables (including RFM variables) and additional customer variables to predict partial churn behavior. Their findings revealed that past purchase behavior variables, particualrly RFM variables are the best predictors of parital customer defection. Also, they confirm the importance of demographic variables and some additional variables such as the length of customer relationsihp, which are also useful to be incorporated in the attrition models.

Suh et al. (1999) proposed RFM as a method that has a low correlation coefficient when combined with neural networks or logistic regression. The findings showed that the combined response model is superior to the single models when the correlation coefficient is low. However, the low correlation coefficient cannnot assure improved performance.

Fader et al. (2005) proposed a model that links RFM with CLV by using iso-value curves so as to visualize the interacitons and trade-offs among the linkage. Besdies, in order to generate valuable informaiton on customer purchasing behavior, by using data collected via a retail chain in Taiwan, Chen et al. (2009) incorproated the concept of RFM in the marketing literature to define the RFM sequential pattern and developed a novel algorithm: RFM-Apriori for generating all RFM sequential patterns from customers' purchasing data.

Hosseini et al. (2010) proposed a procedure according to the expanded RFM model by adding one additional parameter, period of product activity, to classify customer product loyalty under B2B concept. The findings showed that the developed methodology for CRM produces better results than other commonly used models.

Yeh et al. (2008) introduced a comprehensive methodolgoy to select targets for direct marketing from a database by extending RFM model to RFMTC model by adding two parameters, namely: time since first purhcase and churn probability. This model can estimate the probability that one customer will purchase at the next time and the expected value of the total number of times that the customer will purchase in the future. The findings summarized that the proposed methodolgy provides more predictive accuracy than RFM model.

Taking the increasing importance of e-mail in communicating with customers into account, Coussement and Poel (2008) examined whether an extended RFM model (eRFM) and a model adding emotionality related variables from call center e-mails to eRFM model (eRFM-EMO model) can accurately predict customer churn behavior. In their study, eRFM model is referred to as an RFM model by adding socio-demographics and other transactional variables. The findings showed that eRFM-EMO model produces better results than eRFM model. On the other hand, Marcus (1998) simplified RFM model to focus on the customer-value-based variables using only frequency and monetary measures.

King (2007) suggested that when the focus is on citizen segmentation, RFM model should be changed to RFC (recency, frequency and cost) model, as cost is direct financial cost, in providing services to the citizen and indirect quality of life costs to citizen or those affected by the citizen's actions.

SUMMARY

This paper provides a comprehensive review on the application of RFM model. First, this paper depicts the definition and the scoring scheme of RFM. Later, this paper summarizes how RFM model has been applied in various areas. Next, the advantages and disadvantages of RFM model are presented and discussed. Moreover, this paper also elaborates on the relative advantages and disadvantages of RFM and other models. Finally, this paper reviews the articles about the extended RFM to show how RFM can be combined with other variables and other models.

The review on RFM model is essential and can provide fruitful insight to researchers and decision makers. In fact, RFM model has been proven to be very successful in a variety of practical areas. Therefore, RFM can help identify valuable customers and develop effective marketing strategy for not only profit organizations (including marketing industry, banking and insurance industries, telecommunication industry, travelling industry and on-line industry), but also non-profit organizations and government agencies.

For researchers, they can get a full understanding on the overview of RFM model so that they can have more ideas on the refined application of RFM. On the other hand, decision makers can identify valuable customers and develop important strategy by adopting RFM. As a matter of fact, RFM facilitates decision makers to observe customer behavior (Buckinx and Poel, 2005), segment customers (Hughes, 1996; Kahan, 1998), estimate the response probability for each offer type (Spring et al., 1999), calcuate customer value and customer lifetime value (Liu and Shih 2005a; Sohrabi and Khanlari, 2007) and evaluate on-line reviewers (Li et al., 2010). Particularly, direct marketing has a long history in using RFM model (Tsai and Chiu, 2004). Therefore, through the review of the application of RFM model, decision makers would gain insights on RFM and would be able to apply RFM more effectively to resolve the problems encountered in daily activities and develop effective strategy to satisfy a wide variety of customer needs.

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