

# A Study on the Applications of Data Mining Techniques to Enhance Customer Lifetime Value

CHIA-CHENG SHEN<sup>1</sup>, HUAN-MING CHUANG<sup>2</sup>

<sup>1,2</sup> Department of Information Management

National Yunlin University of Science and Technology

123 University Road, Section 3, Douliou, Yunlin 64002, Taiwan, R.O.C.

TAIWAN

[g9623806@yuntech.edu.tw](mailto:g9623806@yuntech.edu.tw)

<http://www.mis.yuntech.edu.tw/>

*Abstract:* - In today's competitive environment, a successful company must provide better customized services, that are not only acceptable to customers but satisfy their needs as well, in order to survive and succeed in gaining an advantage against competition. It has been proven by many studies that it is more costly to acquire new customers than to retain old ones. Consequently, evaluating current customers in order to enhance their lifetime value becomes a critical factor to decide the success or failure of a business.

This study applies data from customer and transaction databases of a department store, based on the RFM model, and does clustering analysis to recognize high value customer groups for cross-selling promotions.

Study findings show that clustering analysis can locate high value customers, and the company can then apply appropriate target marketing to enhance their lifetime value effectively. The implication for the marketer is that leveraging techniques of data mining can make the most from data of customers and transactions databases and thus create sustainable competitive advantages.

*Key-Words:* - RFM, Customer Lifetime Value, Analytical Hierarchy Process, Target Marketing, Data Mining

## 1 Introduction

Because today's businesses are faced with increased complexity and competition, companies must develop innovative marketing activities that both meet and exceed customer needs and improve customer satisfaction and retention. Businesses can benefit significantly by analyzing customer data to determine preferences and improving marketing decision supports. Providing adequate support to meet customer needs can boost the success of on-line e-stores [27] and website success depends on enhancing information and service quality to serve customers better [28].

Recently, IT has been utilized to help companies maintain competitive advantage [15]. Data mining techniques [4] are widely used information technology for extracting marketing knowledge and further supporting marketing decisions [1], [2], [13]. Market basket analysis, retail sales analysis, target market analysis, and cross-selling analysis are included. So, the knowledge can support marketing decisions and customer relationship management.

From the perspective of niche marketing, all customers are not equal, even if they purchase identical products; market segmentations are

therefore necessary. Firms are increasingly recognizing the importance of the lifetime value of customers [29]. Several studies have considered the use of CLV. Generally, recency, frequency, and monetary (RFM) methods have been used to measure it [30], [31]. The concept has been applied to cluster customers for niche marketing [32].

The department store industry must understand and utilize specific customer information; where customers are, how to transmit information to the customer, and the goods information for customers. So every department store issues membership cards or joint name cards in succession, in order to obtain the customer's basic personal data and their purchasing situation. However, it is often extremely difficult to find and even understand the purpose of this important data as it is often hidden deeply within the complex database.

Above all, the purposes of this study are: (1) Assess customer lifetime value (CLV). (2) Improve customer lifetime value (CLV) by target marketing. (3) Improve customer lifetime value (CLV) by cross-selling.

## 2 Literature review

### 2.1 Customer relationship management

The focus of CRM is to forge closer and deeper relationships with customers. Being willing and able to change your behavior toward an individual customer based on what the customer tells you and what else you know about the customer [24]. The premise being that existing customers are more profitable than new customers; that it is less expensive to cross-sell incremental products to existing customers.

Because attracting new customers is expensive, retaining customers is essential. Customer retention would be maximized by matching products and levels of service more closely to customers' expectations. The central objective of CRM is thus to maximize the lifetime value of a customer to the organization [25]. In essence, traditional static CRM is about analyzing customer information for business decisions with the aim being to help organizations understand customers' needs. But differences between customers can be determined via market segmentations that imply that some customers are more profitable than others [26]. It predicts likelihood of customer churn; performs analysis of customer loyalty and profitability, channels effectiveness and profitability, and sales campaign performance [26].

### 2.2 Customer lifetime value analysis and RFM

Customers of the company should be loyal, that is, to buy the products or services of the company repeatedly. The core parts of CRM activities are to understand customers' profitability and retain profitable customers [18]. To cultivate the full profit potentials of customers, many companies already try to measure and use customer value in their management activities [19], [20], [21]. Therefore, many firms are needed to accurately assess their customers' value and build strategies to retain profitable customers.

To the company, the value produced by such a result must be calculated through customer's lifetime value. Many studies have proven that it is more costly to acquire than to retain customers [8], [11], [16]. So, the most critical factors that determine a company's success or failure are evaluating customer's CLV and retaining the most valuable

customers. The definition of CLV is the net present value (NPV) of the future profit that can be created at a particular duration [16]. Customer lifetime value (CLV) is typically used to identify profitable customers and to develop strategies to target customers [33]. Measuring RFM is an important method for assessing customer lifetime value.

Bult and Wansbeek [3] defined the terms as: (1) R (Recency): the period since the last purchase; a lower value corresponds to a higher probability of the customer's making a repeat purchase; (2) F (Frequency): number of purchases made within a certain period; higher frequency indicates greater loyalty; (3) M (Monetary): the money spent during a certain period; a higher value indicates that the company should focus more on that customer.

Many studies have discussed the evaluation of CLV. Hughes [7] proposed a method for RFM scoring by using RFM data to sort individuals into five customer groups. Different marketing strategies could then be adopted for different customers. Goodman [5] suggested that the RFM method avoided focusing on less profitable customers, allowing resources to be diverted to more profitable customers. Stone [14] suggested that different weights should be assigned to RFM variables depending on the characteristics of the industry. In analyzing the value of customers who used credit cards, he suggested placing the highest weighting on the Frequency, followed by the Recency, with the lowest weighting on the monetary measure.

This study approves Stone's view that different weights should be assigned to RFM variables depending on the characteristics of the industry. But because the appointed weighting system was created subjectively by Stone it may affect overall objectivity and produce insufficient results. So to prevent this possible problem, this study uses the decision support tool of the group to improve the objective rationality of appointed RFM weight.

### 2.3 Target marketing and cross-selling

The traditional purpose of marketing has been to achieve success in sales, market share, and gross margin in the marketplace. Increasingly, however, top management have begun to require that marketing view its ultimate purpose as enhancing customers returns [22], [23].

In target marketing, the seller knows and separates the main market district, and then selects

one or more among them to separate for the goal district. It is its guest of development that makes the products melting or marketing scheme [9]. Compared with traditional marketing (Mass Marketing), relation marketing allows companies to concentrate on the important aspect of increasing opportunities to satisfy customers. Traditional marketing placed an emphasis on a particular product to expand the share of market. It was a *single* product that personnel paid attention to, while relation marketing emphasizes the share of customers.

The goal of relation marketing is the share of the customer. So, companies continually make great efforts to sell not only more products but better ones, as well as more frequent and better service. To reach this goal, companies often market high price products to present or potential customers. This is called “up-selling”, which is the most popular tool in cross-selling. Cross-Selling can be defined as the complementary products marketing to the present customer [16].

## 2.4 Analytical hierarchy process

Analytical hierarchy process was a multi-goal decision making method, by professor of Pittsburgh University (Thomas L. Satty) in 1971. Utilizing institutional framework to establish and influence mutual hierarchical structures of the relation, enables us to make valid decisions on complicated problems, make valid decisions under the uncertain risks, or seek consistency in the diverse judgement.. The three main steps of the AHP are as follow: (1) Perform pairwise comparisons; (2) Assess the consistency of pairwise judgments; (3) Computing the relative weights [12].

### 2.4.1 Perform pairwise comparisons

This asks evaluators (decision makers) to make pairwise comparisons of the relative importance of RFM variables using the scale as shown in Table 1 [10].

Table 1. Relative degree of importance for pairwise comparisons

| Comparative importance | Description                                    | Explanation   |
|------------------------|--|---|
| 1                      | Equally importance                             | Two activities contribute equally to the objective  |
| 2                      | Intermediate between equal and weak            | Experience and judgment slightly favor one activity over another                                |
| 3                      | Weak importance of one over another            | Experience and judgment slightly favor one activity over another                                |
| 4                      | Intermediate between weak and strong           | Experience and judgment strongly favor one activity over another                                |
| 5                      | Essential or strong importance                 | Experience and judgment strongly favor one activity over another                                |
| 6                      | Intermediate between strong and demonstrated   | An activity is strongly favored and its dominance is demonstrated in practice                   |
| 7                      | Demonstrated importance                        | An activity is strongly favored and its dominance is demonstrated in practice                   |
| 8                      | Intermediate between demonstrated and absolute | The evidence favoring one activity over another is of the highest possible order of affirmation |
| 9                      | Absolute or extreme importance                 | The evidence favoring one activity over another is of the highest possible order of affirmation |

#### 2.4.2 Assess the consistency of pairwise judgments

Evaluators will make inconsistent judgments when making pairwise comparisons. Before the weights are computed, the degree of inconsistency is measured by an inconsistency index value. Perfect consistency implies a zero inconsistency index value. However, perfect consistency is not often achieved, since people are often biased and inconsistent, when making subjective judgments. Therefore, an inconsistency index value of less than it is acceptable. If the inconsistency index value exceeds this, then the pairwise judgments may be revised before the weights of RFM are computed [10].

#### 2.4.3 Computing the relative weights

This determines the weight of each decision elements. This work employs eigenvalue computations to derive the weights of the RFM. For example, in the Liu and Shih study, three groups of evaluators judge the RFM weightings: three administrative managers, two business managers in sales, and one marketing consultant, and five customers who had previously made at least one purchase. These groups were invited to evaluate the relative importance of the RFM variables.

According to the assessments, the relative weights of the RFM variables are computed [10]. The implication of the RFM weightings is that recent is the most important variable; so evaluators must mainly concentrate on regularity of customer purchasing. If some perform no transactions for a long period, they may have been lost or transferred to new vendors [10].

#### 2.5 Data mining

Data Mining is a knowledge discovery process of extracting previously unknown, actionable information from databases. In detail, it is the non-trivial extraction of implicit, previously unknown, and potentially useful information from data. In other words, it is the search from relationships and global patterns that exist in databases, but are "hidden" among the vast amounts of data. These relationships represent valuable knowledge about the database and objects in the world [17].

Data mining is a multi-disciplinary research and application area that aims to discover novel and useful knowledge from vast databases, using methods ranging from artificial intelligence, statistics, and databases [6]. Data mining techniques have traditionally been used in domains that have structured data, such as customer relationship

management in banking and retail. The focus of these techniques is the discovery of unknown but useful knowledge that is hidden within such vast data. Data mining explores information or knowledge from the patterns. Modern enterprises often collect a large number of patterns, including important information such as the market, customer, supplier, rival, and trends for the future. With data mining, one can successfully navigate through the complex and comprehensive data to find useful knowledge to make decisions, and enhance enterprise competition advantage.

### 3 Methodology

#### 3.1 Company's profile of the case

Case company (I company) applies 'Know-How' from foreign countries, manages with the prospective tactics that coincide development of the society, and emphasizes on consumers' demands and service. The target customers are those ranging from 18 to 35 years old mentally with definite taste. Customers are treated with respect, care, and professionalism. The management of I company focuses on the pursuit of youth fashion and creation, which makes the company consistently attractive to its customers.

I company also realized that making customers loyal to the company and being versatile to the consumers' demands in this competitive industry is the main goal of the company. In order to solve the problems, the company proposed "Loyal Plan for I company", which started in May, 2005. The strategy at the first stage lay in expanding the number of credit card holders to over 100,000. The number of card holders in May, 2005 was 8,399, and then in June it was about 17,236. Till December of 2005, the number was about 46,982.

Finally, in March, 2007, there were over 100,000 card holders, which meant that the company had reached their goal. However, after quantity was achieved, the next stage focuses on quality. I company placed emphasis on stabilizing the good customers. Because, after all, the main goal of I Company is more than a having a large number of card holders, it is ultimately a plan to create customer loyalty and value.

### 3.2 Study design

Figure 1 shows the structure of this study.

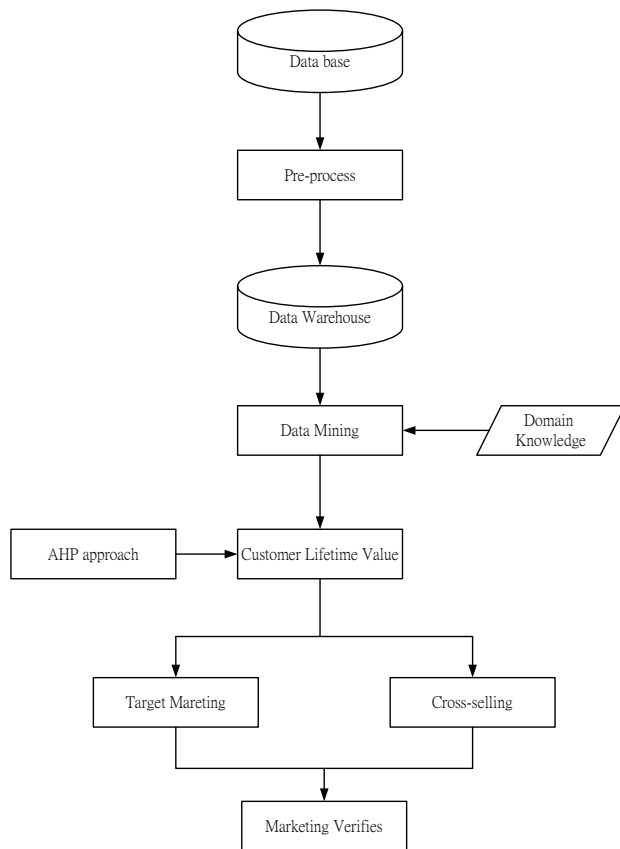


Fig.1 Structure of the study

### 3.3 Data mining process

This study adopts RFM module of customer's consuming behavior analysis as the way a business evaluates customer's value and loyalty to distinguish customers effectively, and find out the target customer. Clustering analysis of Intelligent Miner and correlation analysis are used to do data mining based on the data provided previously and the application of the domain knowledge.

## 4 Analyses and results

### 4.1 Assess customer lifetime value

RFM analytic approach is used to evaluate customer's loyalty and the contribution in the field of marketing management, and is the main tool used in this study for assessing customer's lifetime value. The operational definition of RFM in this study is showed in Table 2.

In order to further utilize IBM Intelligent Miner, this study processed relevant customers and trade information forms in Informix database, and then calculated and extracted R, F, M value of customer's data via Informix SQL. Finally, it changed the files into text, and facilitated the follow-up procedures. The experimental subjects of this study are 52,813 customers altogether from October of 2006 to March of 2007. The data base includes the following seven items: ID number, card number, zip code, trade date, machine number, serial number, and amount of trading money.

Table 2. RFM definition

| Construct         | Means  | This study defines   | Units   |
|-------------------|--|--|---------|
| R<br>(Recency)    | The lastest data one purchased                       | The total days between the day of the latest purchase and analysis | days    |
| F<br>(Frenquency) | The number of purchases made within a certain period | Consuming frequency  | times   |
| M<br>(Monetary)   | The money spent during a certain period              | Amount of money of total consuming                                 | dollars |

In addition, three executive managers of I company were interviewed with AHP to decide the weight of RFM, and to decide the relative weight of RFM in this industry through the software Expert Choice. The software yielded the results of  $W_R=0.059$ ,  $W_F=0.463$ , and  $W_M=0.477$ , while the consistency co-efficiency was 0.00084, which matched with  $C_R < 0.1$  representing that the process of calculation is reasonable. The possible reason might be that the timing of purchases is easily influenced by a promotion such as an anniversary.

After getting the relative weight of RFM and the RFM of an individual customer, a consumer's lifetime value can be calculated by the following steps [10]:

**Step1: Standardize each customer's RFM value**  
Because each of the units of RFM is different, standardization is necessary. The formulae are shown in Table 3.

**Step2: Calculate each customer's CLV**  
Multiply each customer's RFM value times its weight to get an integrative CLV score, and show as formula (1).

$$C'_x = W_R X'_R + W_F X'_F + W_M X'_M \quad (1)$$

Table 3. Standardized formula of RFM

| Construct   | Formula                      |
|---|------------------------------|
| R   | $x' = (x^L - x)/(x^L - x^S)$ |
| F   | $x' = (x - x^S)/(x^L - x^S)$ |
| M   | $x' = (x - x^S)/(x^L - x^S)$ |
| <p><b>Explanation</b></p> <ol style="list-style-type: none"> <li><math>x'</math> and <math>x</math> represent standardized and primitive RFM value respectively.</li> <li><math>x^L</math> and <math>x^S</math> represent the largest and smallest of the R, F or M value of customers group respectively.</li> <li>R value formula for shoulder to relation, x value little <math>x'</math> that change value loud, in the same pace with F, M value.</li> </ol> |                              |

$C'_x$  = Specific customer CLV

$X'_R$  = Specific customer's standardized R value

$X'_F$  = Specific customer's standardized F value

$X'_M$  = Specific customer's standardized M value

**Step3 : Calculate the CLV of each cluster**

The customers' standardized values of each cluster were added together, and then divided by the number of customers of each cluster to get the average values shown as  $C_R^j$ ,  $C_F^j$  and  $C_M^j$  shows  $j=0 \dots 7$ . Then, a CLV value can be derived after multiplying the weights as shown in formula (2), respectively.

$$C_I^j = W_R C_R^j + W_F C_F^j + W_M C_M^j \quad (2)$$

$C_I^j$  = CLV of cluster j

$C_R^j$  = Average of standardized R of cluster j

$C_F^j$  = Average of standardized F of cluster j

$C_M^j$  = Average of standardized M of cluster j

#### 4.2 Utilize Target marketing to improve CLV

After checking the measurement method of CLV for accuracy, customers based on CLV can be divided by RFM value to identify the customers with higher CLV value, and calculate the limited marketing resources to optimize the application. The steps and result of the cluster analysis by using Intelligent Miner, and the application and revelation on marketing are discussed in the following.

In this study, RFM analysis is used to evaluate customer's CLV and loyalty, and therefore identify the target customers with high CLV by clustering analysis. The result of clustering analysis by Intelligent Miner is as follows: Table 4 shows that cluster 0, 1, and 3 belong to customer group 1, about 32.03%, of which the customers are loyal, the so called "best customer group". Companies regard those as VIP, keep good relationships with them, provide related information to them, and respect them as they increase the value of the company.

Table 4. The customer grouping based on CLV

| Group    | Cluster | RFM speciality | Rate (%) |
|----------|---------|----------------|----------|
|          | 0       | high/high/high | 11.12    |
|          | 1       | high/high/high | 9.69     |
|          | 3       | high/high/high | 11.22    |
| Subtotal |         |                | 32.03    |
|          | 2       | high/low/low   | 12.21    |
|          | 4       | high/low/low   | 17.05    |
|          | 5       | low/low/low    | 10.03    |
|          | 6       | low/low/low    | 10.66    |
|          | 7       | low/low/low    | 18.03    |
| Subtotal |         |                | 67.98    |

Table 5. The detailed statement promotion activities

|        |   |
|--------|---|
| Target | All card holders of group1 and group2   |
| Time   | April 14, 2007 to May 8, 2007   |
| Way    | <ol style="list-style-type: none"> <li>1. Get a gift with 500 points</li> <li>2. 100-dollar vouchers for those who spend at least 3200 dollars. 200-dollar vouchers for those who spend at least 5000 dollars.</li> <li>3. Participation in the Lottery activity is allowed for those who spend at least 2500 dollars.</li> </ol> |

The rest of the cluster belongs to customer group 2, about 67.98%. In contrast, they are not helpful to the company's income. Therefore, the managers of marketing have to take the resources allocation of the company into consideration before making decisions. The effect of a company using data mining is shown by empirical analysis in this section. During April 4, 2007 to May 8, 2007, the company had a promotion of sending DM for all card holders. The details of the promotion are shown in Table 5.

Clustering data were put into Informix Database, and confirmed the selling record with clustering data by SQL. Table 6 shows the record of card holders.

Table 6. Table of card holders' purchase record

| Group    | Cluster  | Customers | Customers who purchase | Amount of money |
|----------|----------|-----------|------------------------|-----------------|
|          | 0        | 5,875     | 2,893                  | 15,898,502      |
|          | 1        | 5,116     | 3,448                  | 38,261,490      |
|          | 3        | 5,923     | 2,039                  | 11,786,997      |
| Subtotal |          | 16,914    | 8,380                  | 65,946,989      |
|          | 2        | 6,447     | 2,079                  | 7,480,629       |
|          | 4        | 9,002     | 1,612                  | 5,529,010       |
|          | 5        | 5,297     | 1,143                  | 5,223,455       |
|          | 6        | 5,631     | 833                    | 2,762,107       |
|          | 7        | 9,522     | 1,241                  | 4,817,419       |
|          | Subtotal |           | 35,899                 | 6,908           |
| Total    |          | 52,813    | 15,288                 | 91,759,609      |

Table 7. Comparison of the data from the groups (1)

| Group | Customers | Customers who purchase | Back rate (%) |
|-------|-----------|------------------------|---------------|
| 1     | 16,914    | 8,380                  | 49.54         |
| 2     | 35,899    | 6,908                  | 19.24         |
| Total | 52,813    | 15,288                 | 28.95         |

Cluster 0, cluster 1, and cluster 3 belong to the customer group 1 which is the target customer group (Customers, 16,914) (Customers who purchase, 8,380) (Amount of money, 65,946,989). Cluster 2, cluster 4, cluster 5, cluster 6, and cluster 7 belong to the customer group 2 which isn't the target customer

group (Customers, 35,899) (Customers who purchase, 6,908) (Amount of money, 25,812,620). Tables 7 and 8 show the comparison of the data from the groups.

Table 8. Comparison of the data from the groups (2)

| Group | Amount of selling | Average consuming amount |
|-------|-------------------|--------------------------|
| 1     | 65,946,989        | 7,870                    |
| 2     | 25,812,620        | 3,737                    |
| Total | 91,759,609        | 6,002                    |

Table 9. The district separates CLV comparison sheet

| Section | CLV Cluster | Before promoting | After promoting | Difference |
|---------|-------------|------------------|-----------------|------------|
|         | 0           | 0.0751           | 0.0981          | 0.0230     |
|         | 1           | 0.1105           | 0.1329          | 0.0224     |
|         | 3           | 0.0617           | 0.0786          | 0.0168     |
| Average |             | 0.0825           | 0.1032          | 0.0207     |
|         | 2           | 0.0603           | 0.0698          | 0.0094     |
|         | 4           | 0.0500           | 0.0607          | 0.0107     |
|         | 5           | 0.0335           | 0.0446          | 0.0111     |
|         | 6           | 0.0342           | 0.0426          | 0.0085     |
|         | 7           | 0.0116           | 0.0226          | 0.0110     |
| Average |             | 0.0379           | 0.0481          | 0.0101     |

In this study, consumer's loyalty was assessed by the back rate, about 28.95% of card holders. Whereas, interests was assessed by the average amount of money spent by card holders, about 6,002 dollars. In these groups, the back rate was 49.54%, however, the average amount of money spent was 7,870 dollars, 1.31 times of all of the cluster (1,868 dollars more).

It is obvious that the customers found through data mining could be target ones. Tables 5 and 6 verify

that, by data mining, customers who contribute to the company's income can not only be found, but actually help to decrease the cost of marketing, and thus increase the interest.

In addition to the derivation of the differences of the CLV of clusters before and after promotion, the increase or decrease of CLV was further analyzed by grouping customers as shown in Table 9.

## 5 Conclusion and suggestion

### 5.1 Conclusion

This study adopts the analysis module of RFM consumer's behavior, which is often used to assess the relationship of consumer's loyalty and contribution in marketing. First, assess the weights of R, F, and M in order to know their relative importance by AHP method. Then, sort customers by Artificial Neural Network SOM method to determine the target clusters. After that, target customers' characteristics of purchasing are derived by correlation analysis for marketing units to elevate consumers' loyalty and value, and therefore, enhance their satisfaction. In addition, the CLV classification helps us to recognize each cluster's grade as an important reference for the resource allocation of a business. Based on the result of analysis in this study, some conclusions are proposed as follow:

(1) Based on the result of clustering analysis, the number of target customers with high loyalty, high interest, and a high amount of purchase is about two thirds of the total. Whereas, the amount of target consumers' purchases is about 72% of the total amount in marketing result, and the back rate is about 50%. The result shows that clustering does indeed help to maintain customers. Based on the idea of 80/20 of consumer's relation management, marketing units must try hard to retain those customers who are the foundation of the company interest.

(2)The results show that target marketing is useful in the increase of the customer's CLV. The better the effects, the higher the loyalty, interests, the more frequent the purchase, and the more the amount of purchase.

### 5.2 Suggestion

According to the conclusions above, marketing units must realize that making good use of data mining,



using the company's customer data and records of purchase, can definitely improve the company's competitiveness.

The study offers some suggestions for relevant studies in the future as follows:

(1) Consumer's satisfaction can be studied through telephone interviews or questionnaires on cluster 1 (high loyalty) and can be an important reference for maintaining those customers;

(2) This study provides a quality assessment on clustering and is thus the recommended system for companies. The deeper assessment of recommended quality on a specific product, such as cosmetics, is another way for advanced study;

(3) This study employs the customers' data and consumers' records of purchase of the general merchandise industry as a real case study; the study in different industries will have different problems. So, CLV elevation in different industries is a future direction for further study.

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