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Customer relationship management in the hairdressing industry: An application of data mining techniques

Jo-Ting Wei [a], Ming-Chun Lee [b], Hsuan-Kai Chen [c], Hsin-Hung Wu [d,*]

[a] Department of Business Administration, National Changhua University of Education, Changhua, Taiwan, ROC
[b] Department of Business Administration, National Changhua University of Education, Changhua, Taiwan, ROC
[c] Department of Culture-Based Creative Design, National Taitung College, Taiwan, ROC
[d] Department of Business Administration, National Changhua University of Education, No. 2 Shida Road, Changhua City 500, Taiwan, ROC

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ABSTRACT

With the increase of living standards and the sustainable changing patterns of people's lives, nowadays, hairdressing services have been widely used by people. This paper adopts data mining techniques by combining self-organizing maps (SOM) and K-means methods to apply in RFM (recency, frequency, and monetary) model for a hair salon in Taiwan to segment customers and develop marketing strategies. The data mining techniques help identify four types of customers in this case, including loyal customers, potential customers, new customers and lost customers and develop unique marketing strategies for the four types of customers.

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1. Introduction

With increasing living standards and the sustainable changing patterns of people's lives, people, particularly for the women, spend more on improving their beauty so as to fulfill successfully their roles in various socioeconomic categories. Hairdressing is a common way for people to present a well-groomed face to the world (Kéïta et al., 2005), which mostly refers to the following services-haircuts, hairstyles, hair perming, hair color, hair care and scalp massages (Gerson, 1999).

According to the Economist (2003), Americans spend more each year on beauty than they do on education. The global beauty industry is growing at up to 7% a year, more than twice the rate of the developed world's Gross Domestic Product (GDP). Among all beauty products, the hair-related products are the most usual ones for people to use. Brown and Beale (2008) also indicate that hair-related products comprise the majority of the product amount in the global beauty industry and the hairdressing industry has multi-billion dollar impact on the American economy. In the same vain, Central Statistical Office (1995) points out that people in the UK spend over £2 billion annually on hairdressing services, which almost doubles what it pays annually for dental, medical, nursing and optical fees.

Based on the survey made by Directorate-General of Budget, Accounting and Statistics, Executive Yuan, Taiwan, until May 2010, the national employment for the service industries comprises approximately 60% of the total national employment. In 2009, the service sector's contribution in GDP is composed of 44% of GDP in all industries. At present, in Taiwan, the hairdressing industry is one of the popular service industries for the women when choosing their occupations. Hairdressers must receive the basic hairdressing certificate and can earn higher wage than ever before. Contrary to the traditional values for the hairdressing industry, the hairdressing industry is not a low-skilled and low-waged industry anymore.

The hairdressing industry has become a highly competitive industry in developed and developing economies, showing that the hairdressing industry has significant impact on the economy in developed and developing countries (Brookes & Smith, 2009; Picot-Lemasson, Decocq, Aghassian, & Leveque, 2001). There is no exception to Taiwan. Particularly, an aging population in Taiwan is growing rapidly now. People with higher age demand more frequently to change their hair styles and increase more services to disguise their graying hair. Hence, the importance of the hairdressing industry in Taiwan is increasingly growing. Taiwanese hairdressing industry has the urgent need to identify profitable customers and retain loss customers so as to effectively market the services (Wang, 2010).

Despite of the above and a plenty of management studies examining marketing strategies for the service industries (Beckett, 2000; Rafalski, 2002), prior literature rarely investigates how the customer relationship management (CRM) is implemented in the hairdressing industry and thus there is little known about the marketing strategies of the hairdressing industry. Investigating customer behavior facilitates hair salons to make marketing

* Corresponding author. Tel.: +886 47232105.
E-mail address: hhwu@cc.ncue.edu.tw (H.-H. Wu).

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strategies according to particular demand of customers for the services (Brown & Beale, 2008). Hence, it is vital to provide examinations on how hair salons target valuable customers and make marketing strategies for different types of customers by observing customer behaviors to segment customers. For example, by observing customer behaviors, when finding that particular customers visiting a certain hair salon more frequently and more recently whereas spending less than others would expect more to cope with their dry hair, the hair salon can make particular marketing strategies for the customers such as providing the newest promotional activities and recommending preferential products that can effectively improve their hair health so as to increase their consumption in the hair salon.

Nowadays, the ability to generate useful information from data is an important issue for the industrial managers, showing the necessary for industrial mangers to use data mining (DM) techniques to find the hidden and unknown customer information from the abundant customer data and thus achieve effective CRM (Lee & Siau, 2001; Ranjan & Bhatnagar, 2011). It is common for the service industries to utilize information technology such as building CRM information system or applying DM techniques to systematically analyze customer profiles to segment customers and target valuable customers. When service providers understand customer preference, they can develop adequate marketing strategies for customers and thus can meet their demand, enhance their satisfaction for the services and increase their willingness to purchase (Deal & Edgett, 1997; Fu, Chu, Chao, Lee, & Liao, 2011; Kim, 2011; Min, 2006).

Based on the above, this paper adopts DM techniques – combining the self-organizing map (SOM) and K-means methods along with the application of RFM (recency, frequency, and monetary) model to examine a hair salon in Taiwan to effectively identify its valuable customers and develop its marketing strategies. RFM model has been extensively applied in direct marketing to systematically examine existing customer data to analyze their consumption habits, which benefits marketers to identify profitable customers in an effective way and develop adequate marketing strategies and helps marketers to seek ways to retain lost customers (Lumsden, Beldona, & Morison, 2008; Wei, Lin, & Wu, 2010).

The SOM method and K-means method have been widely used to segment customers when using RFM model (Hanafizadeh & Mirzazadeh, 2011; Huang, Chang, & Wu, 2009). Hair salons can know well the linkage between customer characteristics and customer purchasing habits via adopting the DM techniques to systematically examine customer purchasing history and expenditure records and thus they can effectively allocate the resource to customers and make marketing decisions.

The remainder of the paper is as follows. Section 2 provides the literature review on CRM and DM techniques used in this paper. Section 3 reports the methodology used to conduct this study. Section 4 presents the empirical results. Finally, conclusions, managerial implications, limitations and further research are depicted.

2. Literature review

2.1. CRM

With the increasingly changing industrial environment and increasing competition in the service industry, service industrial managers seek to build good customer relationship and add more value to services (Öztaysi, Sezgin, & Özok, 2011). CRM is defined as the adoption of information technology to develop new customers and retain old customers so as to keep long-term and closed customer relationship, which aims to improve customer relationship and thus can help increase customer loyalty, customer retention and customer profitability (Hennig-Thurau, Gwinner, & Gremler, 2002; Swift, 2001).

2.2. SOM and K-means methods

DM techniques are adopted in different areas such as marketing, market segmentation, market demand prediction and fraud in the financial and insurance industry, the telecommunication industry and the tourism industry etc., which have been widely applied to achieve effective CRM so as to help the industrial managers take marketing decisions (Ranjan & Bhatnagar, 2011; Wei, Lin, Weng, & Wu, 2012).

Among DM techniques, SOM and K-means methods are common methods to cluster groups. Cluster analysis is used to identify a set of groups that both minimize within-group variation and maximize between-group variation according to a distance or dissimilarity function (Witten & Frank, 2005). SOM is a popular unsupervised neural network methodology to clustering for problem solving (Wang, 2001) and market screening (Fish & Ruby, 2009). The SOM network is trained by an unsupervised competitive learning algorithm, which can automatically detect strong features in large data sets and thus produce two-dimensional arrangement of neurons from the multi-dimensional space. Originally, its patterns in a high-dimensional input space are very complicated. After clustering, its structure on a projected graphical map display becomes more transparent and more understandable (Churilov, Bagirov, Schwartz, Smith, & Michael, 2005).

K-means method is one of the commonly seen techniques of clustering algorithm, which involves two main steps, first to place the instances in the closest class (the assignment step) and then re-calculate class centroids from the instances assigned to the class (the re-estimation step) (Huang et al., 2009; Wu, Lin, Liao, & Shieh, 2008). The formula of K-means method typically expressed by Euclidean distance is depicted below. The distance between any two points X_r and X_s, as shown in Eq. (1), can be described by the square root of the sum of the squared distance over each coordinate, and $X_r = (x_{r1}, x_{r2}, x_{r3}, \ldots, x_{ri}, \ldots, x_{rn})$ and $X_s = (x_{s1}, x_{s2}, x_{s3}, \ldots, x_{si}, \ldots, x_{sn})$, where each c_i represents the weight. When the weights are normalized, then $\sum_{i=1}^{n} c_i = 1$ (Abidi & Ong, 2000; Wu et al., 2008).

$$d(X_r, X_s) = \left[\sum_{i=1}^{n} c_i (x_{ri} - x_{si})^2\right]^{1/2} \tag{1}$$

Despite of the advantages of SOM, as other traditional cluster analysis methods, SOM technique does not provide measures for validation of the cluster analysis results (Wang, 2001). It is difficult to find clustering boundaries from the result of SOM. Furthermore, K-means technique is sensitive to the choice of a starting point for partitioning the items into K initial clusters (Chang, Huang, & Wu, 2010; Hosseini, Maleki, & Gholamian, 2010; Kuo, Ho, & Hu, 2002). Due to the weakness of SOM and K-means method, prior literature proposes to adopt a two-staged clustering method (Abidi & Ong, 2000; Chiu, Chen, Kuo, & Ku, 2009; Vesanto & Alhoniemi, 2000). In this regard, this paper applies the K-means technique to find the clustering boundaries from results of SOM. In the first stage, data set is clustered via adopting the SOM to decide the number of data clusters (k). In the second stage, the derived approximation of the clusters (k) determined in the first stage is used with K-means method.

2.3. RFM model

RFM model is a behavior-based model to analyze and then predict customer behaviors based on the past customer behavioral activities in the database (Wei et al., 2010). It consists of three measures, namely recency, frequency, and monetary, which are combined into a three-digit RFM cell code. Recency measures the number of periods since the last purchase (e.g., days or months). Frequency measures the number of purchase made in a particular time period. Monetary measures the total amount of money spent during a particular period of time.

A common way to adopt RFM model to analyze customer behavior is to sort the customer data via each dimension of RFM and then divide them into five equal segments. For recency, the customer database is sorted based on purchase dates by descending order. For frequency and monetary, sort customer visiting frequency data and the customer purchasing data in descending order, respectively. The top 20% segment is coded as 5. The next 20% segment is assigned as a code 4 and so on. Accordingly, all customers can be presented by 555, 554, 553, ..., 111 with possible 125 ($5 \times 5 \times 5$) RFM cells (Hughes, 1994; Kahan, 1998). Another approach is to use the original data rather than coded numbers (Chang et al., 2010). That is, recency is the time length since the most recent purchase; frequency means the number of purchases during the same time period; and monetary refers to the total amount of money spent on all purchases. In this study, we adopt this approach for RFM model.

3. A case study

The transaction data were from January 1, 2008 to March 31, 2008, i.e., the first quarter of 2008, with 9620 transactions by 789 customers from a particular professional hair salon in Taiwan. Each transaction includes the customer's membership number, purchase date, purchase item, product category, item price, item quantity purchased, and total purchase amount of money. The definitions of recency, frequency and monetary are as follows. Recency is defined as the most recent purchase in the database. Specifically, recency measures the number of days since the last purchase from January 1, 2008 to March 31, 2008. In this study, January 1, 2008 is given by a number of one, January 2, 2008 is assigned by a number of two, and March 31, 2008 has the value of 91. To transform the data set into frequency, count the number of purchase for a particular customer in the first quarter of 2008. Finally, monetary is measured by computing the total amount spent in this quarter for a particular customer.

The descriptive statistics regarding the maximum, minimum and average values of recency, frequency, and monetary values are summarized in Table 1. The maximum and minimum recency values are 91 and 1, respectively. For the frequency, the maximum and minimum values are calculated to be 28 and 1, respectively. The maximum and minimum monetary values are calculated to be $102,776 and $125 (calculated in New Taiwan Dollars), respectively.

Fig. 1 shows that eleven clusters are recommended by SOM. Later, the number of clusters of K-means method is set to eleven and applied in RFM model. Table 2 summarizes the sample size, average recency (R), average frequency (F), average monetary (M), and the symbol of R, F, and M above the average. By observing Table 2, if the average R (F/M) value of a cluster exceeds the total average R (F/M) value, then an upward arrow ↑ is shown; otherwise, a downward arrow ↓ is shown. Clusters 1, 4, 10, and 11 have R, F, and M values greater than the average R, F, and M values (R↑F↑M↑), representing the customers in these clusters have high contribution to this hair salon, defining as loyal customers. For this type of customers, regularly sending latest catalogs, understanding their shopping habits and their needs through the transactions and actively using mobile phone text messages to provide suitable information and limited time offer for new products are the means to increase their loyalty.

Table 1
The descriptive statistics of recency, frequency and monetary.

	Maximum	Minimum	Average	Standard deviation
Recency	91	1	61.7	25.2
Frequency	28	1	3.2	2.8
Monetary	102,776	125	5225.8	7818.3

In addition to Clusters 1, 4, 10, and 11, Cluster 9 has higher R and F values but lower M value compared to the average R, F and M values (R↑F↑M↓). The customers in Cluster 9 have high response rates, defined as potential customers. They purchase recently and frequently such that the hair salon can actively contact these customers by increasingly sending the number of product catalogs along with promotional activities and a variety of free gifts. The major intention is to increase both customers' interest in purchasing the products and the amount of money spent.

Cluster 5 has higher R value but both F and M values are less than the average values (R↑F↓M↓). The customers in Cluster 5 belong to new customers. They shop recently and have the potential to be the loyal customers for the long-term perspectives. The hair salon should enhance customer relationship by keeping touch with the customers and seek ways to meet their demand so as to attract them to visit more often and purchase more. For example, the hair salon can provide these customers special services such as special discount to possibly encourage them to shop more frequent and spend much more money.

Finally, Clusters 2, 3, 6, 7, and 8 have smaller R, F, and M values compared with the average values (R↓F↓M↓). The customers in these clusters belong to loss customers. In order to retain these customers, some marketing strategies can be made by the hair salon such as ultra-cheap merchandise mix offers and discount coupons to strengthen the relationship between the hair salon and customers.

By further studying the most frequent purchased items for the customers in each cluster, Table 3 depicts the information based on the transactions data. Most customers tend to purchase nourishing conditioner products, hair color and related products, permanent-related products and hairstyles-related products.

Customers in Clusters 1, 4, 10, and 11 mainly purchase shampoos-oily scalp and nourishing conditioners, indicating that these customers pay much attention to hair cleaning, hair health and hair shining. Customers in Cluster 9 prefer to purchase shampoos-oily scalp, nourishing conditioners and essence serum, pointing out that these customers emphasize hair cleaning and hair health and particularly care deep penetrating for hair so as to prevent from dry hair. Customers in Cluster 5 often purchase hair color kit–brown, nourishing conditioner and paste, showing that these customers frequently change hair color, pay attention to hair care after hair color and love to keep particular hair styling via using paste. Customers in Clusters 2, 3, 6, 7 and 8 frequently purchase the following products, including hair spray, permanent waves, permanent for frizzy hair and profession repair solution, representing that these customers care the quality of hair curling solution, products that can make repair for damaged hair and hairstyles after hair curling.

4. Conclusions, managerial implications, limitations and further research

The hairdressing industry has played an increasingly important role in the service industries. Nowadays, it has become a large, attractive industry (the Economist, 2003; Brown & Beale, 2008; Kéïta et al., 2005). However, little research examines the marketing strategies of hairdressing industry, revealing a need for further

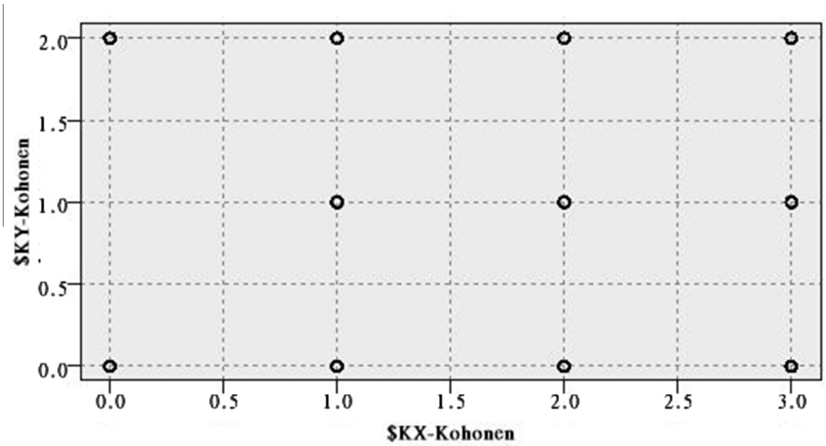

Fig. 1. Eleven clusters generated by the SOM method.

Table 2
The clustering results by SOM and K-means methods.

Cluster	Sample size	Average R	Average F	Average M	Symbol(s) above average
1	33	68.66	5.51	9920.24	RFM
2	119	60.08	2.18	3223.60	–
3	149	18.96	1.26	1396.45	–
4	2	87.50	27	97197.5	RFM
5	203	79.58	2.02	2836.20	R
6	46	47.32	1.58	2022.28	–
7	66	47.32	1.58	2022.28	–
8	33	32.57	2.27	2793.90	–
9	32	72.96	3.78	5130.28	RF
10	83	84.61	7.42	11726.32	RFM
11	23	83.95	11.47	27775.17	RFM
Total	789	61.68	3.20	5225.82	

Table 3
The most frequent purchase items for customers in each cluster.

Cluster	Most frequent purchase items for each cluster
1	Shampoo–oily scalp, hair color kit–brown, and conditioner
2	Therapy serum, hair spray, shampoo, and hair color
3	Essence serum, permanent waves, hair spray, permanent for frizzy hair, and professional repair solution
4	Shampoo volume and nourishing conditioner
5	Hair color kit–brown, nourishing conditioner, and paste
6	Paste, professional repair solution, and permanent for frizzy hair
7	Nourishing conditioner, hair color kit – brown, and shampoo–oily scalp
8	Permanent for frizzy hair, permanent waves, and hair mousse
9	Shampoo–oily scalp, nourishing conditioner, and essence serum
10	Nourishing conditioner, shampoo–oily scalp, hair color kit–brown, and hair color
11	Nourishing conditioner, essence serum, and hair color

understanding. DM techniques help to uncover the hidden and unknown information from abundant data (Ranjan & Bhatnagar, 2011), which have been extensively applied in service marketing and effectively helps identify and understand customer preference and further meet customer demand. This paper adopts RFM model by applying a two-stage clustering method suggested by prior literature (Abidi & Ong, 2000; Chiu et al., 2009; Vesanto & Alhoniemi, 2000) by combining SOM and K-means techniques to systematically analyze customer profiling for a hair salon in Taiwan. The examination on customer profiling via RFM model assists the hair salon to know the preference and the purchasing habits for different types of customers and thus assists the hair salon to make particular marketing strategy for a particular type of customers.

In this paper, eleven clusters are formed by SOM technique and then adopted by K-means technique to apply in RFM model. The analysis results of RFM model indicate that the customers in the hair salon can be grouped into four types of customers, i.e., loyal customers, potential customers, new customers and lost customers. Marketing strategies for the hair salon are suggested in accordance with the four types of customers in this paper.

Management literature asserts that shaping customers perceptions of services is vital, showing that the overall image created by the service providers can significantly influence service quality and further influence customers' choices of the service providers (Ince & Bowen, 2011; Xiao & Nicholson, 2011). For loyal customers in the hair salon, it is critical to provide highly customized services, build the transactions record system, periodically follow the customer expenditure trend and send the newest product information via personal telephone or e-mail to achieve good customer relationship. In addition, providing free trials for particular products is also an essential way to give feedbacks to the customers. On the other hand, since this type of customers prefer to make hair cleaning, hair health and hair shining, the hair salon can actively select nourishing conditioner and shampoo with purifying scalp and oily scalp for the customers. Moreover, the hair salon can provide free consultations for hair care and scalp problems such as pruritus, dandruff and alopecia.

The major marketing strategies for potential customers are to provide them the news about recent promotional activities and special services for hair treatment. Examining customer transactions data to know customer purchasing behavior facilitates the hair salon to adopt a cross selling strategy, to know which products suitable to be recommended and to be given preferential prices to the customers. Furthermore, the hair salon can also provide gifts or discount with the purchase of a target amount, via the above marketing methods, the hair salon can motivate the customers to enhance their purchasing amounts and thus increase the profitability. On the other hand, the potential customers highlight shampoos-oily scalp, nourishing conditioners and essence serum, suggesting that the hair salon can encourage customers to increase the use of the following services, including hair cleaning, deep hair repair treatments and the products that can prevent from dry hair, so as to help customers improve scalp health and enhance deep hair treatment.

In order to increase the purchasing amount of new customers, the hair salon can adopt promotional channels such as certificate and interest-free installment. Besides, the hair salon can also develop a closer and longer relationship with the customers via such as providing a more comfortable service environment to keep the customers stay longer. Furthermore, to provide a free parking and free hair consultations might also be the suggested strategy to strengthen the interaction of the hair salon with the customers. This type of customers prefers to change hair color, use nourishing conditions and keep particular hairstyles via paste. Hence, the hair salon can also offer the customers vegetable hair color, hair treatment for dry hair and paste that help maintain natural and long-term effect.

The lost customers in the hair salon are customers needed to be retained by the hair salon. For this type of customers, the hair salon can adopt convenient and cheap marketing channels such as sending the e-paper and mobile phone text messages about the promotional news and providing economy products to attract the customers. To make advertisement is also a feasible way to convey the image of the hair salon and a crucial factor to influence the customers' decisions about whether to stay in the hair salon since the quality of hairdressing services only can be assessed during and after the purchase of the services. As this type of customers often purchase particular products for hair care and hairstyles, the hair salon can provide the customers economy, good-quality and healthy hair spray and curling lotion and the services for treatment of damaged hair.

The DM techniques in this paper help systematically examine customers profile and segment customer types and thus facilitate to develop unique marketing strategies for each type of customers in the hair salon. This benefits the hair salon to effectively target valuable customers and implement differential marketing strategies. This paper only includes particular customer data and may thus provide limited marketing implications to managers. Liston-Heyes and Neokleous (2000) document that gender-based pricing exists in the hairdressing industry, suggesting that investigating customer demographic characteristic may provide different marketing implications. Hence, examining customer demographic characteristics or their real perceptions about hair care and hair styling, information such as the age, the gender, the education background, the occupation, waiting time of services, hair treatment and modern styling equipments might be needed for the hair salon to improve its overall services.

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