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An Extended LRFMP Model for Customers Segmentation by Using Two-Step SOM: A Study of Aesthetic and Dermatology Center

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ABSTRACT

To recognize customers, organizations use a scale to measure the importance of different customers. In the present study, the customer segmentation is done in the aesthetic and dermatology center in an Islamic country based on the extended LRFMP model. For attaining the purpose, this study used clustering by Two-Step SOM and data gathered from 220 patients of aesthetic and dermatology center in an Islamic country. Due to selecting the optimal number of clusters, is adopted the Davies-Bouldin index. In the first step, the number of clusters is calculated by Lehman's rule, and then by the SOM method, the analysis was repeated for three, four, and five clusters and through the Dunn index compared the results. Also, for more understanding, the type of patients has selected the label for the clusters by using Marcus's customer value matrix as the foundation. Considering the value of the Dunn index, the triple cluster is the favorite cluster. The status of LRFMP indices was shown in the triple cluster, and selected the labels for each cluster as "Loyal customers", "Potential loyal customers" and "Uncertain customers". Regarding the nature of the labels and the literature, this study recommended marketing strategies. The investigation of the kinds of the literature showed that segmentation in the aesthetic and dermatology center in an Islamic country was not performed with LRFMP indices by SOM in an aesthetic and dermatology center.

Keywords

Customer segmentation, LRFMP model, Customers clustering, Two-Step SOM.

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1. Introduction

Customer relationship management (CRM) was introduced in the early 1980s and includes four dimensions: customer recognition, customer attraction, customer retention, and customer development. Through CRM, the firms can manage their interaction with customers (current and potential), and it cusses opportunities for the companies to gain competitive superiority in a competitive environment. Vincent (2016) believed three crucial decisions should be made in strategy development: segmentation, positioning, and target market selection. Market segmentation has enticed the considerations during the last 50 years. Smith (1956) proposed the definition of market segmentation for the first time (Boejgaard and Ellegaard, 2010). Besides, Buttle and Maklan (2015) mentioned that customer data is trapped in the organization's pockets and not operational to potential users. Right customer recognition in competitive markets has become vital to any business. Segmentation is when a company categorizes its customers within a market into similar groups by considering specified characteristics, desires, and needs (Hunt and Mello, 2014).

On the other hand, customer segmentation is a way that an organization can recognize the customers better, and ultimately resource allocation is optimized. As Vincent (2016) believes, a marketing mix (Price, Product, Place, and Promotion) helps understand the customers' needs and provide the value to determine the particular actions. By segmentation, marketing managers and marketers respond to customers better and present proper marketing strategies for each group of customers. Judging the customer's value on one aspect gives an imprecise report of the customer base and lifetime value. A more in-depth comprehension of the customers has accredited the importance of focusing on them. It is accepted that it expenses about five times more to reach a novel customer than to retain an existing one and ten times more to get a discontent customer back (Massnick, 1997). In addition, Reichheld (1996) believed that five-point growth in customer retention could accelerate incomes by more than 25%. According to Marcus (1998), small- to mid-sized businesses are better at creating excellent customer relationships. Focusing on direct marketing allows organizations to allocate their marketing resources to gain more return on investment and compete more effectively to retain their customers. In this way, they can develop and grow their business, which causes good customer relationships. Also, Marcus (1998) believed that for small and mid-sized self-governing businesses, it is better to focus their marketing program on local relationship marketing due to actively using their competitive advantage. Pooya et al. (2020)

mentioned that effective organizations gain customer satisfaction. Customer retention in the long term is more profitable than attracting new customers. So, the retention strategy for loyal customers involves finding and understanding how the customers are satisfied. This article investigates the kinds of literature in two directions: the research of segmenting and its indices, and the second, the methods of segmenting and clustering.

In the first direction, there are many methods for segmenting customers. The most popular method for segmenting the customers is RFM, proposed by Hughes in 1996. The RFM (recency, frequency, monetary) model is a marketing technique that ascertains quantitatively that customers are the desirable ones by analyzing how recently a customer has bought (recency), how many times they bought (frequency), and how much the customer pays out (monetary). There have been numerous efforts to improve segmentation variables, and additional variables have been added to each industry. For example, Yeh et al. (2009) proposed an expanded RFM model by adding two parameters, time since first purchase and lost Customer probability. By utilizing the Bernoulli sequence in probability theory, they discovered the formula that estimated the likelihood that a customer buys and the total number of times a customer comes back to buy. They examined a blood transfusion service to note that their methodology has precise predictive accuracy compared to the traditional RFM approaches. According to Reinartz and Kumar's (2000)'s study, the RFM model cannot determine the length of time a customer is related to the organization (short or long term); they introduced customers' relationship length in their research. Also, they examined the effect of customer loyalty and profitability, and finally, they completed the RFM model by the Loyalty index by presenting the LRFM model.

Wei et al. (2012) used the developed LRFM model in Taiwan. They segmented patients (according to the patient profile, such as gender, membership number, birth date, and visit frequency). Also, another research on Customer Relationship Management in the Children's Dental Clinic used the Two-Step Algorithm. Finally, the customers are divided into loyal, new, and lost Customers. Chiang (2018) extended the RFM model to the RFMDT model (D variable is the abbreviation of discount; T variable is the abbreviation of the shopping times in six months). The case of Chiang's study was online shoppers in Taiwan. Moreover, Peker et al. (2017)'s opinion; is that people tend to visit various sectors like hotels, clinics, and hair salons more frequently, which advances the level of variation in their visiting patterns, which is essential in explaining their purchasing behavior.

In the second direction, various customer or retailer segmentation studies utilize the clustering model, such as taxonomy models and SOM. Pooya and Faezirad (2017) presented a study to distinguish the taxonomy of manufacturing strategies from manufacturing competitive precedents and the taxonomy of production processes in a developing country. Also, they adopted SOM to identify common patterns. The relationship between production processes and manufacturing strategies was studied using Crosstabs and the chi-square test. Khajvand et al. (2011) researched customer lifetime value estimation based on RFM analysis of customer purchasing behavior. They used customer lifetime value (CLV) to segment a customer in a health and Beauty Company using two extended RFM and RFM approaches by Count Item. The results showed that Count Item did not make any difference in customer clustering. Wei et al. (2012) conducted the application of the LRFM model on the segmentation of the dental clinic market, which aimed to recognize customers; and exceptionally loyal customers. For this purpose, they studied 2258 patients, and the monetary value variable was considered constant due to the provision of government support services. Their research shows that three clusters are above the average LRF values. Peker et al. (2017) proposed LRFP for classifying customers in the grocery retail industry and segmentation. Li et al. (2011) surveyed customer characteristics of a textile factory by a two-stage clustering method based on the LRFM model. The Ward index determined the optimum number of clusters, segmented customers into five clusters using K-means, and analysis of each cluster's attributes using the LRFM scoring method. Alizadeh Zoeram and Karimi Mazidi (2018) proposed a new approach for customer clustering by integrating the LRFM model and the Fuzzy Inference System. They attempted to provide a systematic method for analyzing the characteristics of customers' purchasing behavior to improve the operation of the customer relationship management system. For this purpose, the extended model of LRFM was used that would be proper for analyzing the customer lifetime value.

The results of their study are five different customers group that they named high-contribution loyal customers", "low-contribution loyal customers", "uncertain customers", "high spending lost customers", and "low-spending lost customers". Parvaneh et al. (2014), in their study, utilized data mining due to segment the retailers of hygienic manufacturers. They proposed the LRFMP model for retailer segmentation. Their study results are ten retailer clusters using the K-means algorithm with K-optimum. Also, the weighted sum of LRFMP values by the AHP technique. Alipour Sarvari and Takci (2016) investigated that the customers segmented by attention to the RFM model by utilizing artificial intelligence methods, including k-means clustering, Apriori association rule mining (ARM), and neural networks. Their study noted demographic factors because they wanted to present different scenarios due to improved factors for segmenting the customer.

Hammer (1983) mentioned that grown competition prompted many physicians to consider serious attention to how they can utilize modernized marketing methods to enhance the flow of patients to their clinics. By examining studies in clinics, studies in this field (Aesthetic clinics and other clinics) show that clinics cannot succeed in utilizing marketing methods as worthy. The studies in clinics such as Kamagahara et al. (2016) focused on dental clinic management in Japan, where the service quality enormously influences the clinic's outcome. Also, Van et al. (2010), in their study, developed a marketing strategy for engaging at-risk individuals with Internet-based depression inhibition interference in primary care by targeting essential attitudes.

As mentioned, various types of research on the segmentation of customers according to the RFM model (and extended of it) through utilizing the multiple methods in the different industries. This study has proposed the LRFMP model and segmented the customers using the self-organizing mapping method (SOM), a neural network-based clustering method. The Self-Organized Mapping Network can perform the learning process on complex and multidimensional data. This method helps extract a visible cluster set (Kohonen, 1998). In fact, to our knowledge, no research has been done on customer clustering concerning the LRFMP indices by Self-Organized Mapping Network in an Aesthetic & Dermatology Center, so this is one of the innovations of the present study. The Aesthetic & Dermatology Center provides various aesthetic & dermatology services to patients. These centers are customer-oriented firms, and the people who visit these centers, like their age or any reason, see different ups and downs in their appearance. They worried about it increasingly because of various reasons. Therefore, each segment of customers helps better recognize the customers for providing customer service. This recognition leads to customer relationship targeted, marketing management, and appropriate resource allocation. On the other hand, help Aesthetic & Dermatology Centers provide professional and complimentary consultation before and after the services. This paper is organized as follows: research method, finding, discussion, cluster labeling, conclusion, and theoretical and practical implications.

2. Methodology

By examining the background of the research and interviewing organizational experts, attention was paid to the LRFMP indices, and all the indices have the same importance. So, this study aims to evaluate and cluster the Aesthetic & Dermatology Center customers based on the LRFMP model indices. This article has been done on customer segmentation in one of Mashhad's Aesthetic & Dermatology Centers. The center has been operating since 2011, and this study gathered data from 220 patient samples from 2018 until 2020; they have come to the clinic for any service. Data collected included the age, the date of the first and last visit, the number of visits, patterns that the patient came to the clinic, and the time and cost of paying. The L index, which represents the length of time a patient related to the clinic (or the patient's loyalty), was calculated by comparing the first and the last visit dates. The maximum of the L index is 84 months (84 months are the clinic's age till now). The R index represents the more recent patient visits, calculated by subtracting the last time the patient visited from the end of 2019.12.22. The maximum of the R index is 458 days.

The F index is defined as the number of times the patient has visited the clinic, and the M index shows the total cost spent on the clinic by the patients, which these data were recorded on their profile cards. The P index represents the patterns the patient came to the clinic (or Periodicity) extracted from the customer database. The operational steps of the research method of this study are as Figure1.

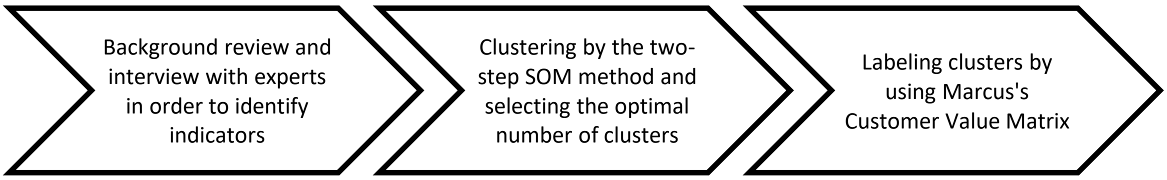

Figure 1. Operational steps of the research method

The clustering in this study was done by the two-step SOM method. Clustering is one of the most important data mining methods, especially in marketing research. Many methods have been developed for data clustering; one is the SOM or Kohonen map. It is a neural network-based clustering method that is an unsupervised learning model. In other words, the SOM presents a mapping from a higher-dimensional input space to a lower-dimensional map space. Placing a vector from data space onto the map is to detect the node with the vector of the closest weight to the data space vector (Ultsch and Siemon, 1990). It is fundamentally a method for dimensionality reduction, and it maps a higher-dimensional input to a lower-dimensional discretized representation (Kohonen, 1998). Due to selecting the optimal number of clusters, one of them is the Davies Bouldin index, the silhouette width, or the Dunn index. In this study was used the Dunn index (1).

$$DI = \min_{1 \le i \le k}\{\min_{i+1 \le j \le k}\{\frac{d(C_i.C_j)}{\max_{1 \le l \le k} diam(C_l)}\}\} \tag{1}$$

Where $d(C_i.C_j)$ denotes the distance between the cluster *i, j,* and $diam(C_l)$ represents the diameter of cluster l. Each of these two parameters is computed using equations (2) and (3):

$$d(C_i.C_j) = \min_{x \in C_i . y \in C_j} d(x.y) \tag{2}$$

$$diam(C_l) = \max_{x.y \in C_l} d(x.y) \tag{3}$$

The diameter of a cluster (equation (3)) is the maximum distance between two cluster members, and the distance between two clusters (equation (2)) is the distance closest to the two members. Therefore, the more the Dunn index value helps ensure well-separated and compacted clusters. Lehman (1979) suggested that the number of clusters is between n/30 and n/60, where n is the sample size. Therefore, in the first step, the number of clusters is calculated by Lehman's rule between three and five clusters, and then by the SOM method, the analysis was repeated for three, four, and five clusters. After that, the Dunn index compared the results and determined the best number of clusters. Also, for more understanding, the type of patients has selected the label for the cluster. Labeling clusters was done using Marcus's Customer Value Matrix as the foundation. According to Marcus (1998), the Customer Value Matrix requires primary customer and buying data.

3. Findings

3.1. Results of the clustering by two-step SOM method

As mentioned in this study, data was gathered from 220 samples of patients from 2018 until 2020 that have come to the clinic for any service, then the clustering of customers was analyzed through the SOM method. For this purpose, due to the five LRFMP properties, the number of neurons was considered once 3, once 4, and once 5. As a result, three, four, and five clusters are achieved.

The three clusters. The position of clusters, their neighborhood status, and the number of members in each cluster are illustrated in Figure 2:

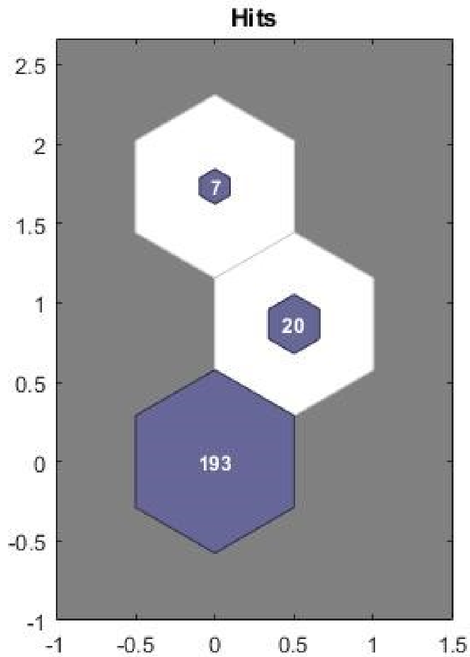

Figure 2. The three cluster

Table (1) shows the coordinates of the centers of each of the three clusters. The coordinates of each center are specified for each of the five dimensions of the LRFMP. The value of the Dunn index for these clusters is 0.044.

Table 1. The centers' coordinates of three clusters

	L	R	F	M	P
The first cluster	18.77	49.78	2.33	465.69	0.22
The second cluster	28.11	43.74	5.74	4018.42	0.37
The third cluster	13.60	15.60	9.40	7780	0.60

The four clusters. The position of clusters, their neighborhood status, and the number of members in each cluster are shown in Figure 3:

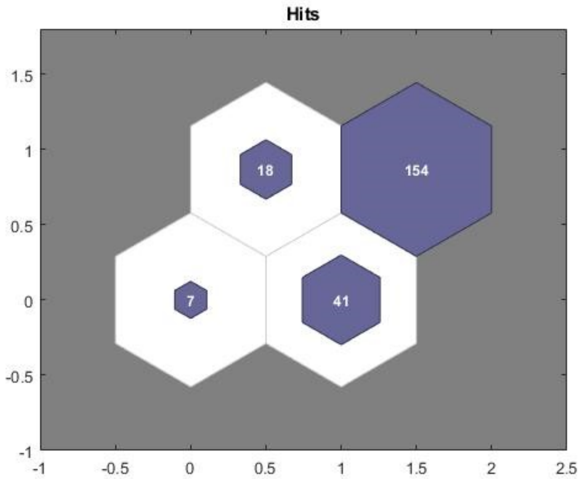

Figure 3. The four clusters

Table (2) illustrates the coordinates of the centers of each of the four clusters. The coordinates of each center are specified for each of the five dimensions of the LRFMP. The value of the Dunn index for these clusters is 0.0058.

Table 2. The centers' coordinates of four clusters.

	L	R	F	M	P
The first cluster	13.60	15.60	9.40	7780.00	0.60
The second cluster	22.30	44.35	3.46	1284.59	0.46
The third cluster	29.39	34.44	6.17	4091.67	0.37
The fourth cluster	15.37	49.39	1.97	268.72	0.18

The five clusters. The position of clusters, their neighborhood status, and the number of members in each cluster are illustrated in Figure 4:

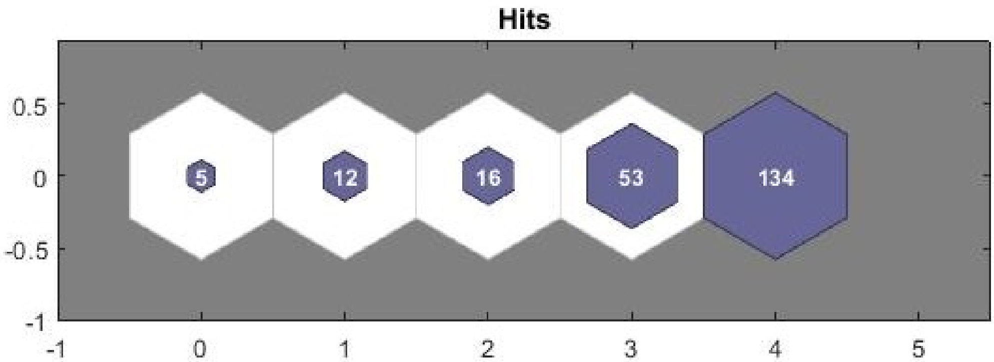

Figure 4. The five clusters

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Table (3) shows the coordinates of the centers of each of the five clusters. The coordinates of each center are specified for each of the five dimensions of the LRFMP. The value of the Dunn index for the five clusters is 0.0061.

Table 3. The centers' coordinates of five clusters

	L	R	F	M	P
The first cluster	13.333	15.33	10.66	8466.66	1
The second cluster	23.33	14.50	6.25	5016.66	0.33
The third cluster	29.33	62.66	4.73	2643.33	0.27
The fourth cluster	19.98	27.78	3.29	902.15	0.52
The fifth cluster	17.41	57.18	1.86	225.54	0.12

3.2. The final clustering

Considering the value of the Dunn index in the status of the three clusters is the highest in comparison to the other type of clusters. Therefore, the proposed final clustering with the three clusters can be considered. As mentioned, the data of the LRFMP indices were gathered from 220 patients. Table 4 shows the average of each LRFMP indices for all patients:

Table 4. The average of the LRFMP indices of all patients

	L	R	F	M	P
The average	19.54	46.69	2.79	1028.72	0.26

Table 5 illustrates more information about triple clustering.

Table 5. The information of triple clustering

Cluster	The number of patients	The average of L	The average of R	The average of F	The average of M	The average of P	The average of age	More than average
3	7	32	58	8.42	8557.14	0.53	29	LFMP
2	20	23.9	27.05	5.55	3877.5	0.34	35.9	R
1	193	18.63	48.31	2.29	460.46	0.23	33.78	-
Average		19.54	46.7	2.78	1028.7	0.2579		

4. Discussion and cluster labeling

As shown in Table 5, the L index represents the length of time a patient interacts with the clinic (or the patient's loyalty); the third cluster has the highest rank compared to the other clusters. The third cluster has the highest rank in the F index, which showed the number of times patients came to the Aesthetic & Dermatology Center. Furthermore, the third cluster has the highest rank in the M index, offering the patients' total cost spent on the clinic despite the lowest number. The P index represents the patterns in which the patient came to the clinic. The win of the third cluster in most indices belongs to 29 years, but the age of almost 36 years that got soon to the Aesthetic & Dermatology Center belongs to the second cluster. Although the third cluster has the highest score in most indices, the lack of an R index is worrying. The paucity of R index means some patients did not visit recently, so the Aesthetic & Dermatology Center lost their big spender and frequent customers, or some of the patients used specified services. Finally, the R index representing the more recent patient visits is calculated by subtracting the last time the patient visited from 2019.12.22. Therefore, the best R index is a cluster with a lower value, so the second cluster is the winner in the R index. The winner in the R index, while the second cluster is the loser in the other indices, means the newcomers are in the second cluster. As observed in Table 5, although the first cluster is the highest number of patients (approximately 87% of the total patients but 39% of the total revenue), this cluster is the misfit cluster because it could not get a proper position in any LRFMP indices. In Table 5, the "More than average" column was utilized to select the cluster label according to Marcus's (1998) article.

The third cluster is exalted in the LFMP. It means the loyal patients, the patients who frequently go to the center, the big spenders, and the periodic patients who came to the clinic but did not visit recently belong to this cluster. So was assigned the Loyal Customers as a label to the third cluster. Also, the potential loyal customers as the label were selected as the second cluster related to fresh customers. Finally, the first cluster is the highest in the patient numbers, but all the indices' loser was assigned Uncertain Customers as the label.

5. Conclusion

This study aimed to segment the Aesthetic & Dermatology Center customers on LRFMP indices through the SOM method. This paper used the two-stage SOM method for customer clustering with due attention to the LRFMP model in the Aesthetic & Dermatology Center. In the first step, the number of clusters is calculated by Lehman's rule (1979) between three and five clusters, and then by the SOM method, the analysis was repeated for three, four, and five clusters. After that, the Dunn index compared the results and determined the best number of clusters. The result of the Dunn index showed that the triple cluster is the best number of clusters. The label selected the cluster for more understanding types of patients according to their characters in their cluster. The label of clusters was named "Loyal customers", "Potential Loyal Customers" and "Uncertain Customers". The findings show that each Aesthetic & Dermatology Center customer segment should be adopted different behavior. Following presented Theoretical implications and Practical implications.

5.1. The theoretical implications

The findings of this study have implications not only for the study of the Aesthetic & Dermatology industry but also for each service-oriented business due to the importance of Loyalty, Frequency, Monetary, Periodicity, and Recency indices for service-oriented businesses. Most researches focus on the LRFM model for segmenting customers (Reinartz and Kumar (2000), Yeh et al. (2009), Khajvand et al. (2011), Wei et al. (2012)). There are some studies that these studies extended the LRFM model by adding the Periodicity index (Peker et al. (2017)) and the Discount index (Chiang (2018)).

By reviewing the literature, few studied the service-based market segmentation according to LRFMP model indices by SOM or other models. For practical directing and operational usage of the customer data instead of trapping them in pockets within the organization, the literature was perused to propose the appropriate marketing strategies by considering specified characteristics. However, to our knowledge, no studies match the nature of the Aesthetic & Dermatology services. Given the less academic concern in the concept of this study's purpose, this study can contribute to the existing literature by providing valuable insights.

5.2. The practical implications

The finding also has practical implications for service-based firms. According to the developed Peker et al. (2017)'s model, the LRFMP model was adopted to segment the customers to recognize them better and keep a productive relationship with them in the Aesthetic & Dermatology Center. For more understanding, the type of patients has selected the label for the cluster. The label of clusters was named "Loyal customers", "Potential Loyal Customers" and "Uncertain Customers". Each type of customer in the triple clusters follows specific marketing strategies.

Customer retention is vital for any business that creates frequent purchases due to a growth in customer retention that can accelerate incomes (Massnick, 1997; Reichheld, 1996). According to Marcus (1998), small- to mid-sized businesses are better at creating excellent customer relationships. Focusing on direct marketing allows organizations to allocate their marketing resources to gain more return on investment and compete more effectively to retain their customers. In this way, they can develop and grow their business, which causes good customer relationships. Whereas the Aesthetic & Dermatology Center is categorized as small and mid-sized self-governing, it would better focus on retaining and local relationship marketing. Maintaining the customer that belongs to the third cluster (Loyal customers) is vital, as they guarantee business survival. As Pooya et al. (2020) mentioned, effective organizations gain customer satisfaction. Customer retention in the long term is more profitable than attracting new customers. So, the retention strategy for loyal customers involves finding and understanding how the customers are satisfied.

The Aesthetic & Dermatology Center should show in its treatment that loyal customers are worthy. For example, it should consider privileged discounts (for New year) and hold events that loyal customers relate together and the center. Loyal customers should feel they are different from the center, which can be done by sending birthday cards. They are an excellent resource for reinforcing the LFMP indices. A and have the potential to increase the R index.

In their study, Wei et al. (2012) proposed that to increase the number of patient visits, the clinic could serve more after-medical care activities and provide gifts. Parvaneh et al. (2014) mentioned when the firms did the segmentation of customers in their article. They should implement a proper marketing strategy for each cluster. They propose Cross-selling, loyalty programs, and Strong anti-attrition. By doing Cross-selling, sellers increase their income from their customers.

Focusing on patients who have previously visited the center minimized the marketing costs, but they increased the expense of promotion programs. Whereas Loyal customers are big spenders who spend lots of money on the clinic, the fit strategy increases their purchase frequency. Loyal customers have demonstrated loyalty due to the frequency of purchases; the beneficent strategy is to accelerate their purchases; in other words, the functional level strategy could be Push Marketing Strategy. Due to the purchasing behavior of Potential Loyal Customers, they also buy from competitors. By tactic of discounts of regular and periodic visits for these types of customers and tactic of discounts on services due to increasing the variety of purchased services, the center could hope that they become loyal customers and so that the monetary value and frequent purchases will increase. Therefore, the best strategy is to focus the marketing activity on newcomers or depend on a specified service type. The center should try to get these customers away from their competitors with a stair-step volume discount policy; eventually, the Uncertain Customers be converted to another cluster. The monetary value and frequent purchase determine their purchasing pattern and the likelihood that loyal customers increases. Wei et al. (2012) suggested that patients with lower values in the length, recency, and frequency index can be ignored, and the resources should be allocated to valuable customers. However, the Uncertain Customers are the largest group, representing approximately 87% of the total patients but 39% of total revenue.

5.3. Limitations and future research

This study has limitations. The lack of an existing marketing strategy for each type of service the Aesthetic & Dermatology Center provided imposed hardships on recognizing the attribute of the cluster in the initial phase of the study. Also, the unspecific gender of patients on the profile card constrained us from building a clear image of the customer's mind map. The other characteristics of patients should be attention (like educated level and date of birth) that help segment the customer and design a proper marketing strategy. Another limitation is the lack of precise approaches to the marketing mix (especially Price and Promotions) of the Aesthetic & Dermatology Center. It also imposed difficulty for proposing improvement marketing strategy suggestions for each cluster. This article presents the marketing suggestions implicitly. An experimental study helps to understand the marketing strategy's effectiveness better. For example, an investigation can examine which marketing strategy is better and how each cluster's customer behavior is affected. As we know, the marketing strategy belongs to the functional strategy level. So, each business should ensure that the strategy at the practical level aligns with the corporate strategy. The business lives on a different scale, so they should adjust their marketing activity by having a cost advantage and logistics.

Disclosure statement

No potential conflict of interest was reported by the author(s).

References

Alipour Sarvari P, Takci H. 2016. Performance evaluation of different customer segmentation approaches based on RFM and demographics analysis. *Kybernetes, 45*(7), pp.1129 -1157. https://doi.org/10.1108/K-07-2015-0180.

Alizadeh Zoeram A, Karimi Mazidi AR. 2018. A New Approach for Customer Clustering by Integrating the LRFM Model and Fuzzy Inference System. *Iranian Journal of Management Studies (IJMS), 11*(2), pp.351-378. https://doi.org/10.22059/ijms.2018.242528.672839.

Boejgaard J, Ellegaard Ch. 2010. Unfolding implementation in industrial market segmentation. *Industrial Marketing Management, 39*(8), pp.1291-1299. https://doi.org/10.1016/j.indmarman.2010.06.004.

Buttle F. Maklan S. 2015. Customer relationship management: concepts and Technologies. *Routledge, Taylor and Francis Group, United States: New York.*

Chiang WY. 2018. Establishing high value markets for data-driven customer relationship management systems: An empirical case study. *Kybernetes, 48*(3), pp.650-662. https://doi.org/10.1108/K-10-2017-0357.

Hammer J. 1983. How to Promote and Advertise a New or Existing Clinic. *Health Marketing Quarterly, 1*(1), pp.61-67. https://doi.org/10.1300/J026v01n01_08.

Hughes AM. 1996. Boosting response with RFM. *Mark. Tools, 3*(3), pp.4-10.

Hunt CS, Mello JE. 2014. Marketing. *McGraw-Hill Education*, United States: New York.

Kamagahara Y, Takeda T, Jin Sh, Lu X, Ota T, Hara T, Kida N. 2016. Qualitative Analysis of the Customer Satisfaction at the Dental Clinics. *Digital Human Modeling: Applications in Health, Safety, Ergonomics and Risk Management, 9745*, pp.229–242. https://doi.org/10.1007/978-3-319-40247-5_24.

Khajvand M, Zolfaghar K, Ashoori S, Alizade HS. 2011. Estimating Customer Lifetime Value Based on RFM Analysis of Customer Purchase Behavior: Case Study. *Procedia Computer Science, 3*, pp.57-63. https://doi.org/10.1016/j.procs.2010.12.011.

Kohonen T. 1998. The self-organizing map. *Neuro computing, 21*(1), pp.1-6. https://doi.org/10.1016/S0925-2312(98)00030-7.

Lehmann DR. 1979. Market research and analysis, *Homewood Ill by Irwin.*

Li DC, Dai WL, Tseng WT. 2011. A two-stage clustering method to analyze customer characteristics to build discriminative customer management: A case of textile manufacturing business. *Expert Systems with Application, 38*(6), pp.7186-7191. https://doi.org/10.1016/j.eswa.2010.12.041.

Marcus C. 1998. A practical yet meaningful approach to customer segmentation. *Journal of Consumer Marketing, 15*(5), pp.494-504. https://doi.org/10.1108/07363769810235974.

Massnick F. 1997. The Customer is CEO: How to Measure what Your Customers Want and Make Sure They Get It. *Amacom, United States: New York.*

Parvaneh A, Tarokh MJ, Abbasimehr H. 2014. Combining Data Mining and Group Decision Making in Retailer Segmentation Based on LRFMP Variables. *International Journal of Industrial Engineering & Production Research, 25*(3), pp.197-206. URL: http://ijiepr.iust.ac.ir/article-1-529-en.html.

Peker S, Kocyigit A, Eren PE. 2017. LRFMP model for customer segmentation in the grocery retail industrial case study. *Marketing Intelligence & Planning, 35*(4), pp.544–559. https://doi.org/10.1108/MIP-11-2016-0210.

Pooya A, Faezirad M. 2017. A taxonomy of manufacturing strategies and production systems using self-organizing map. *Journal of Industrial and Production Engineering, 34*(4), pp.300-311. https://doi.org/10.1080/21681015.2017.1305996.

Pooya A, Abed Khorasani M, Gholamian Ghouzhdi S. 2020. Investigating the effect of perceived quality of self-service banking on customer satisfaction. *International Journal of Islamic and Middle Eastern Finance and Management, 13*(2), pp.263-280. https://doi.org/10.1108/IMEFM-12-2018-0440.

Reichheld FF. 1996. The Loyalty Effect. *Harvard Business School Press, United States: Massachusetts*.

Reinartz WJ, Kumar V. 2000. On the profitability of long-life customers in a noncontractual setting: An empirical investigation and implications for marketing. *Journal of Marketing, 64*, pp.17–35. https://doi.org/10.1509/jmkg.64.4.17.18077.

Smith WR. 1956. Product Differentiation and Market Segmentation as Alternative Marketing Strategies. *Journal of Marketing, 21*(1), pp.3-8. https://doi.org/10.1177/002224295602100102.

Ultsch, A, Siemon HP. 1990. Kohonen's self-organizing feature maps for exploratory data analysis. *Proceedings of the International Neural Network Conference (INNC-90), Paris, France*, *1*, pp.305-308.

Van Voorhees BW, Watson N, Bridges JFP, Fogel J, Galas J, Kramer C, Connery M, McGill A, Marko M, Cardenas A, Landsback J, Dmochowska K, Kuwabara SA, Ellis J, Prochaska M, Bell C. 2010. Internet-based depression prevention over the life course: a call for behavioral vaccines. *Prim Care Companion J Clin Psychiatry, 34*(1), pp.167-183. https://doi.org/10.1016/j.psc.2010.11.002.

Vincent L. 2016. Marketing Strategies for Commercialization of New Technologies. *In Technological Innovation: Generating Economic Results, 26*, pp.257-287. https://doi.org/10.1108/S1048-473620160000026009.

Wei J, Lin Sh, Weng Ch. 2012. A case study of applying LRFM model in market segmentation of a children's dental clinic. *Expert Systems with Applications, 39*(5), pp.5529-5533. https://doi.org/10.1016/j.eswa.2011.11.066.

Yeh IC, Yang KJ, Ting TM. 2009. Knowledge discovery on RFM model using Bernoulli sequence. *Expert Systems with Applications, 36*(3), pp.5866-5871. https://doi.org/10.1016/j.eswa.2008.07.018.