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A Customer Segmentation Model Proposal for Retailers: RFM-V

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Abstract

Today's businesses have large quantity of demographic, economic and behavioral data on their customers with the rapid development of computer and internet technologies. Customer segmentation analyzes are carried out on the basis of various parameters in order to identify and group consumers with different needs and wishes and to develop marketing applications and solutions specific to each group. RFM analysis is a commonly used and well-known customer value evaluation tool for analyzing and classifying vast volumes of customer data quickly and effectively. It is used to numerically identify the correct customers by examining how recently, how often and to which monetary value a customer has made purchases. This study proposes a new model to be used in customer segmentation. In this model called RFM-V, the "V" parameter indicates the diversity of the customer's purchases, which can define customer depth in terms of customer relationship management literature. The study also proposes a new matrix, Customer-Product Depth Matrix, with this new variable V added to the model. With this matrix created by using M and V parameters, customers can be examined in four quadrants according to their depth. Analysis findings can also be associated with basket analysis data in order to develop healthier marketing strategies and realize effective promotional suggestions.

Keywords: RFM analysis, customer segmentation, customer depth, CRM

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Introduction

With the development of computer and internet technologies, today's businesses have large volumes of databases of demographic, economic, and behavioral data about their customers. With the "big data" formed in these databases, the problem of finding data about the customer that the marketers lived in the 90s and 2000s was eliminated, and it was replaced by the ability to produce "customer information" by combining meaningful pieces of large amounts of data. In industries with many product categories, "data mining" and thus "customer segmentation" play a critical role in many different areas from improving customer service to developing effective sales and distribution strategies, from promotional campaigns to cross-selling practices (Han et al., 2011).

Customer segmentation analyzes are carried out based on various parameters in order to identify and group consumers with different needs and desires and to develop marketing applications and solutions specific to each group. In these analyzes, age, location, income, gender, lifestyle, and previous purchasing behavior variables are commonly used (Kotler&Keller, 2009; Christy et al., 2018). An ideal client segment should be homogeneous internally (i.e. all customers in the segment should have similar preferences and characteristics), but heterogeneous externally. Thus, businesses can distinguish customer groups, determine which customers are more profitable and loyal, and develop different strategies according to these groups (Chang et al., 2015: p.75). The RFM is a commonly used and well-known tool for the analysis and classification of large volumes of customer information for simple and efficient analyzes (Chang et al., 2010: p.809; Cheng & Chen, 2009: p.4178). It is used to numerically identify the right customers by examining the recency, frequency, and monetary value of the purchases a customer has made. It is a customer segmentation technique based on the purchasing behavior parameter because it uses customers' transaction history information. (Chang & Tsai, 2011; Wu & Lin, 2005).

Recent studies show that using additional variables to predict customer behavior can improve the predictability of RFM models (Hosseini et al., 2010; Yeh et al., 2008). For this purpose, this study proposes a new model for more effective customer segmentation. In this model called RFM-V, the "V" parameter indicates the variety of the customer's purchases. With the addition of this variable, which can define customer depth in terms of customer relationship management literature, it is predicted that the model will give better results in determining the customer segments that need to be protected and improved, and developing more appropriate marketing strategies for them. This study also proposes a Customer-Product Depth Matrix with the addition of Variety variable to the model. With this matrix created by using M and V parameters, customers can be examined in four different types according to their depth and monetary values.

Literature Review

Customer Relationship Management

Customer Relationship Management (CRM) is the practice of handling comprehensive customer and contact points information so that customer satisfaction is increased (Kotler & Keller, 2009). The individual marketing and relationship marketing strategies are employed by a company to better understand and administer its clients based on what the customer does, tells, and other knowledge the customer has provided (Peppers, Rogers & Dorf, 1999). Parvatiyar and Sheth say (2001: 5) that CRM is a comprehensive strategy and process to link, retain and cooperate with selected customers with regard to the development and integration of the marketing, sales, customer service and supply chain functions of the company to improve the efficiency and effectiveness of customer value delivery. CRM is a customer-focused management approach to build long-term relationships with profitable customers for companies, as described by Darvish et al. (2012:2). In the literature, it is apparent that there is no widely accepted single definition. American Marketing Association's definition is "a discipline in marketing combining database and computer technology with customer service and marketing communications."

CRM, which begins with the retention of customer data, allows it to segment them with the help of this data and seeks, by providing marketing suggestions suited to each segment, to increase customer loyalty and satisfaction in 3 phase according to the process below:

- Customer identification: Customer segmentation is the first step in implementing a CRM strategy. The objective is to optimize both the consumer interest and the company's sustainable profit by splitting consumers into classes that are best served depending on their characteristics (Freeland, 2003). To increase the value of segments after customers are divided into segments, it is necessary to determine appropriate strategies for each segment and to identify and enforce appropriate processes and structure for each segment (Crockett, 2003). Periodic effects understanding is an important factor of consumer recognition (Kumar & Petersen, 2012).

- With the aggregation of customers, a decision may be taken as to what service the customer group is provided. The RFM analysis (Khajvand et al.' 2011) is one of the commonly used analyses in this context and shows the frequency, value and currency of transactions of customers and will be discussed in detail in the following section. RFM analysis should be used to ensure that concepts of the market value of the customer, such as uncertain customer, profitable customer, daily customer, one-time customer, etc. are understood.
- Establishing customer relationships: At this point, long-term and productive relationships are under way with selected customers. The establishment of long-term relationships is focused on both sides' commitment to cooperation (Doyle, 2003, pp.165-166). Companies also maintain a database of customer information to build and improve customer relationships. The customer can be interacted with special offers while processing these results. In hospitality companies the data in question can, for example, be linked to customers' choices for wine, table preferences, last experience information, etc. Catering companies can contact their special clients directly, invite them to special events, offer them special discounts and provide access to new business services and opportunities (Cosic & Djuric, 2010: 56-57).
- A company's relationship with its clients involves regular bilateral contact and interaction. It can be short- or long-term, temporary or permanent, repetitive or individual, or attitudeary or behavioral. This partnership must be managed by CRM in order for the two parties to benefit each other profitably and mutually. Lifetime customer value is a tool for calculating this relation (Gray et al., 2001: 7-8).
- Customer protection and growth: the protection and growth of the relationships formed with the customer are the last phase and objective of the customer relations management process. The phase is also known as the retention or deepening of the customer relationship (Parvatiyar & Sheth, 2001). Steps are taken to preserve long-term consumer loyalty and profitability and to boost the consumers' expenditure. At this point, the main objective is to achieve new benefits through a continuous partnership. In particular, as research in various sectors demonstrates, the high cost of attracting new clients is leading companies to strategies to protect their current customers (Winer, 2001, Reichheld & Sasser 1990, Peppers & Rogers, 1996, Amin et al., 2017).

Customer transactions can be listed and used in the establishment of vast transaction databases in today's information technology. Marketing analysis and database operations have also begun to be more focused on this technology (Coussement et. Al., 2014). An effective CRM application involves the disclosure of consumer patterns, sections and needs, and the development of a comprehensive customer database (Kotler & Keller, 2009). It has developed and applied several new analyses over the last two decades to obtain customers using customer databases and to ensure customer loyalty and increase profits (Hughes, 2003, p. 17). RFM analysis is one of the most commonly used analyzes.

RFM Analysis

The main purpose of RFM analysis, which is widely used in customer value analysis, is to identify the most valuable customers. The most valuable customers; are the customers who come frequently and spend the most in the nearest time frame. RFM analysis offers businesses the opportunity to develop various campaigns and policies that will increase customer loyalty for each group by categorizing their customer portfolios. Developed by Huges in 1994, RFM analysis is based on analyzing customers' behavior and then making predictions based on their behavior in the database. The analyzes are carried out with three variables measured and combined into an RFM ranking. Recency measures the period since the last purchase (day, month, or year). Frequency estimates the number of transactions in a particular period of time. Monetary tests the cumulative money invested for a certain time or the average purchase expenditure or all acquisitions to date (Wei et al., 2012: p.5530).

In order to measure the RFM value, the original data or encoded values may be used. When calculating the "R" value using the original data, for example, the selected date duration is numbered by increasing a number starting from the farthest date to the nearest date. The "F" value is the customer's number of visits or transactions between these dates. The "M" value is the cumulative sum between these dates spent by the customer. By taking these averages, customers can be broken into segments (Wei, Lee, Chen, & Wu, 2013). In the coded values method, for example, the customer database purchase dates are sorted in descending order for up-to-dateness. 20% of customers who shop from the company most recently are coded as 5, and the other 20% are coded as 4 and so on. Customer visit frequency data and spending amount data are also sorted in descending order. All customers are coded like 555, 554, 553, ..., 113,112,111 (5 x 5 x 5 = 125 probability) according to the percentile in these three dimensions. Thus, the database is divided into 125 equal sets. The most profitable customers are normally those with the highest RFM scores (Hosseini, Maleki, & Gholamian, 2010, Wei et al., 2013).

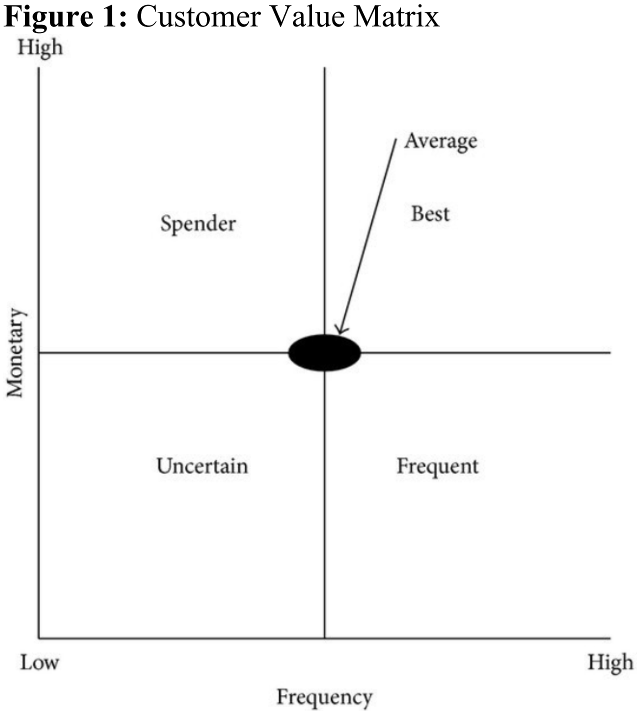
In another technique, the customer list is arranged in reverse chronological order according to the purchase date and divided into five equal parts. Customers who shopped on the closest date are coded with the number "1", and those on the farthest date with the number "5". Creating 5 equal divisions in this way is called "making fifths". Customers are then sorted based on their frequency number order, and the same procedure and labeling process is used. Finally, the same method is applied to the quantities of "average expenditure" (Kahan, 1998).

Chen et al. (2009) proposed a score calculation method that involves deciding lower and upper limits for each RFM dimension. (Rtime minimum) and (Rtime max) are the up-to-dateness limits; they apply to the time interval between the selected sample's starting time and the last operation after the given start time. As a result, if R time minimum: 200 and Rtime max: 270, the selected sample's last processing time should be between 200 and 270 days. Similarly, the expenditure sum must be within the (M minimum) and (M max) values, which are the upper and lower limits for the amount. The percentage of transaction sequences that match the most recent and sum results is known as frequency. RFM findings based on these three parameters include "30% of customers who recently purchased computers will return to buy scanners and microphones, with a total value exceeding $ 50,000" (Chen, Kuo, Wu, & Tang, 2009).

The RFM model is commonly used because it is simple to use, fast to implement, and easy to understand by business managers (McCarty & Hastak, 2007; Kahan, 1998). The key advantage of RFM research for businesses is that it allows them to recognize their best customers. This, however, is just the start of the operation. Analysis can be used to isolate and group customers in addition to developing a simple model of consumer characteristics. For each customer category, cognitive models can be developed, and look-alikes for the best customers can be identified. Furthermore, given that consumers in the same category were grouped together based on previous similar actions, it is possible to assume that they will behave similarly in the future. As a result, instead of targeting all consumers when launching a new marketing campaign, it could be possible to target a certain percentage of each customer group (Kahan, 1998). RFM, being a simple and cost-effective behavioral analysis technique, allows the retrieval of consumer and transaction data that has been processed in an electronic format. RFM makes much more efficient use of electronic information, lowers marketing costs per consumer order, and improves company profitability by integrating behavioral and logical research techniques (Kahan, 1998).

The results of the RFM analysis should match business objectives and show the marketing manager which groups can be combined to create a particular tactic or strategy. Marcus (1998) simplified the RFM analysis and introduced a model in which small retail and service businesses would build consumer clusters to analyze customer values and display them on a matrix, in line with this expectation. Marcus (1998) introduced the "Customer Value Matrix" (Figure1), which performs segmentation by measuring average values for frequency (F) and quantity (M) and displaying the customer value in the matrix.

Figure 1: Customer Value Matrix



It is possible to use a particular marketing approach depending on the area of the matrix where the customer is located. For instance, while suggesting a retention strategy for Top Customers, it also suggests strategies to improve the frequency of transactions for Spenders with a high average purchase potential. Cluster analysis and other classification approaches may be used to perform RFM analysis (COMPAQ, 2001; Im & Park, 1999; Madeira, 2000). These techniques aid in the accurate determination and application of RFM analysis data. Since RFM analysis is used for a variety of purposes by professionals, various managerial advantages can be achieved by different managers (Hosseini, Maleki, & Gholamian, 2010). RFM is used in direct marketing, for example, to examine consumer buying patterns by systematically analyzing existing data. Marketers will more easily classify profitable customers, create marketing plans for them, and look for ways to reclaim lost customers in this way (Wei et al., 2013).

Today, approaches that take advantage of modern technology such as neural networks are challenging RFM analysis. Despite this, direct marketers continue to use RFM analysis. Because despite the high application costs of these alternative techniques, there is no guarantee of the accuracy of the results obtained (Marcus, 1998, p. 494). However, in order to eliminate the limitations of the model, to compete with new data mining methods, and to reach more effective results in terms of segmentation, it is seen that the number of different suggestions about the model has increased in the literature.

RFM-V Model

As criticism of the shortcomings of RFM analysis, especially its inadequacy in the field of forecasting, grows, so does the number of academic studies attempting to improve the model's predictive capacity. Recent research has shown that providing extra variables to RFM models will increase predictive power when modeling customer behavior (Hosseini et al., 2010; Yeh et al., 2008). According to several researchers (e.g., Daoud, Amine, Bouikhalene, & Lbibb, 2015; Chow & Holden, 1997; Kao, Wu, Chen, & Chang, 2011), the basic RFM model never addresses customer loyalty, which is primarily concerned with the customer-company relationship. According to Reinartz and Kumar (2000), the basic RFM model is unable to distinguish between long-term and short-term customers, despite the fact that increasing the length of the partnership improves consumer loyalty. Many researchers attempted to change the model in this direction in response to the criticism of Reinartz and Kumar (2000) that "the RFM model cannot differentiate which customers have long or short term relationships with the business.". Chang and Tsay (2004) built the LFRM model by incorporating the length of the relationship span (L), which is one of the most fundamental measures of consumer loyalty (Wei et al., 2012: p.5529, Wu et al., 2014: p.2, Zoeram and Mazidi, 2018: p.358, Özkan and Deveci Kocakoç, 2019, Özkan, 2020). The L parameter represents the amount of time that has passed since the consumer made their first purchase and their most recent purchase. By combining consumer attributes, the LRFM model attempts to analyze a new customer clustering strategy. In the CRM method, this model is regarded as a new data mining technique (Ngai, Xiu, & Chau, 2009).

The length of the relationship was not the only factor in the studies added to improve the model's ability. For example, Yeh et al. (2008) proposed an updated RFM model that included two additional parameters. The first purchase (T) and the possibility of losing the customer are included in the RFMTC model (C). To address the problem, Chang&Tsai (2011) propose a new paradigm called GRFM (for community RFM) review. The new approach takes into account the characteristics of the purchased goods, resulting in a measured RFM value for consumers that is closely linked to their purchases and accurately reflects their actual consumption behavior.

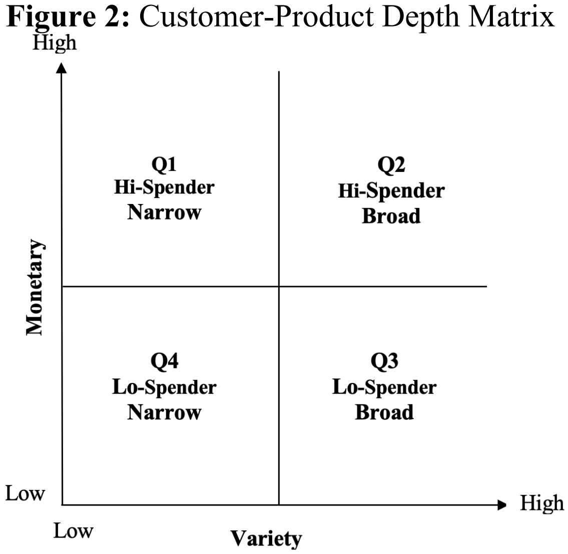
In light of the criticisms and studies mentioned above, this study suggests adding the product variety purchased by the customer to the RFM model as the fourth variable. Thus, RFM-V analysis is presented. In the third phase of customer relationship management, customer development, and deepening, one of the main objectives of the business is to increase the customer's profitability by increasing the customer spending share. In this context, RFM-V analysis will be an important analysis tool to identify customers with high spending shares. This analysis method will contribute to the stock and promotion management activities as retail businesses are businesses that offer services to their customers with a wide variety of product mixes. Customers with similar profiles can display different features in terms of product diversity according to the RFM model. Thanks to this analysis, it will be possible to make a segmentation including these differences.

Table 1: Definitions of Variables in the RFM-V Model

Variables	Definitions
R-Recency	Number of days since the last visit
F-Frequency	The number of visits in a given time
M-MONETARY	The average amount of spending
V-Variety	Number of different products bought

For the RFM-V model, the "Customer-Product Depth Matrix", similar to the "Customer Value Matrix" developed by Marcus (1998) based on RFM analysis, is also recommended. In the matrix created by considering the monetary (M) and variety (V) values, the customers are categorized according to which of the four regions in two axes they are. The matrix is shown in Figure 2.

Figure 2: Customer-Product Depth Matrix



With the help of this matrix, businesses can design different marketing strategies to meet the needs of their different customers. The region where the customer cluster is located in the matrix is determined as a function of the customer spending amount and the variety of products purchased. Customers in the 1st quadrant, called hi-spender narrow, spend a large amount of money despite purchasing a small variety of products from the market. Implementing marketing and sales strategies that will enable customers in this group to purchase more different products will increase the depth of this group. When their depth increases, it is expected that there will be an increase in total expenditure amounts. It is recommended to use basket analysis data and association rules to increase the depth of these customers.

Customers, which are in the second quadrant, are called hi-spender broad. They are the deepest customers of the business. Both the amount of expenditure and the variety of products these customers purchase are high. Preventive marketing strategies are recommended to maintain them. On the other hand, customers who are located in the third quadrant which we call lo-spender broad, purchase many different types of products from the business, but their expenditure amounts are very low. Upselling is recommended to increase the amount of expenditure of this customer group. The customers in the fourth quadrant that we call the lo-spender narrow, spend very little and buy a limited variety of products. It is recommended to consider their position in the customer value matrix to decide what kind of marketing strategy to apply to these customers.

Retailer Case Study for RFM-V Model

The use of the recommended V parameter is very useful in analyzing customers, especially in the retailing sector where membership cards are purchased. The idea of the RFM-V model is based on the practical need of a retailer on customer segmentation. The retailer has a membership card with lots of basket and purchase data. When the data is examined, it is realized that RFM analysis would be a good fit. However, the results of the customer segments formed by basic RFM analysis did not give the retailer a better understanding of the customer clusters. The idea of using product variety as the fourth variable emerged at this point.

In this study, the basket data of customers who have a membership card in all stores in the Aegean Region of a retail chain were analyzed by RFM analysis. The database used in the study includes 60284 unique customers in a data file of 6406485 lines (shopping receipts) covering a 6-month shopping period. The total expenditure amount is 45,136,538.40 Turkish Liras. Customer classification is made by using data such as the customer membership no, the date and time of the shopping, which store (location) the shopping is made from, the size (format) of the relevant store, the description of the purchased products, the class of the purchased products, and the net expenditure. Customers who came only once in the timeframe are removed from the data set. In the analysis, codes written in the R language are used.

As the first step, R, F, M, and V values for each customer are calculated by using real values as in Table1. Descriptive statistics for R, F, M, and V are given in Table 2. V variable defines the number of different products bought by a customer.

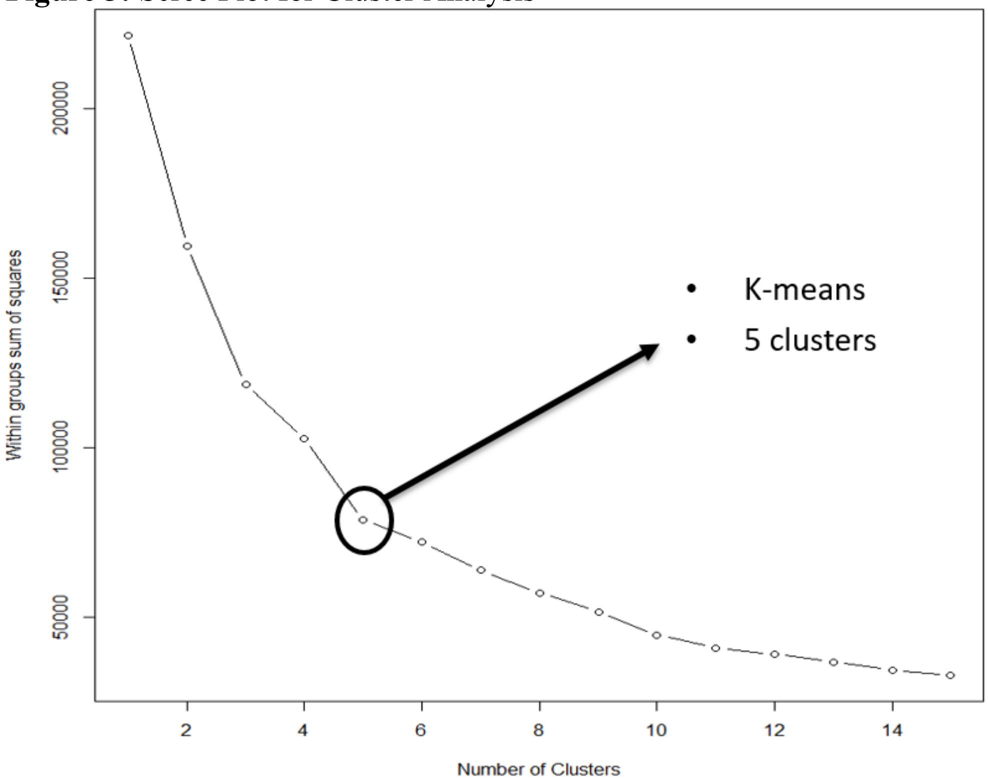
Table 2: Descriptive Statistics of Variables in the RFM-V Model

Statistic	Recency	Frequency	Variety	Monetary
Min.	0.0	2.0	1.0	1.3
1stQ	126.0	5.0	27.0	23.4
Median	165.0	11.0	56.0	40.4
Mean	143.7	17.1	77.1	58.3
3rdQ	178.0	21.0	105.0	71.1
Max.	182.0	283.0	1852.0	9009.4
Std Dev.	47.2	19.6	72.4	93.4

The maximum and minimum values for recency (R) were 182 and 0, respectively. The data is reverse coded so higher values indicate that the customer had recently visited the market. Maximum and minimum values for frequency (F) are calculated as 283 and 2, respectively. The average frequency is 17. The amount of expenditure (M) is calculated as 9009 TL maximum and 58.3 TL on average. The maximum variety is 1852 different products while the minimum variety is 1 as expected.

In order to categorize customers in the matrices in Figure 1 and Figure 2, they must be divided into clusters. K-means cluster analysis is done for four clusters, as suggested by the scree plot in Figure3.

Figure 3: Scree Plot for Cluster Analysis



As the number of clusters increases, the variance (within-group sum of squares) decreases. The elbow represents the most parsimonious compromise between decreasing the number of clusters and reducing the variance within each cluster, with five clusters. This means that as the model's complexity (i.e. the number of clusters) increases, the model's output does not improve significantly. Thus, customers are clustered into five, based on their R, F, M, and V values. A four-cluster solution is also examined and found that the clusters don’t fit well to interpret and use.

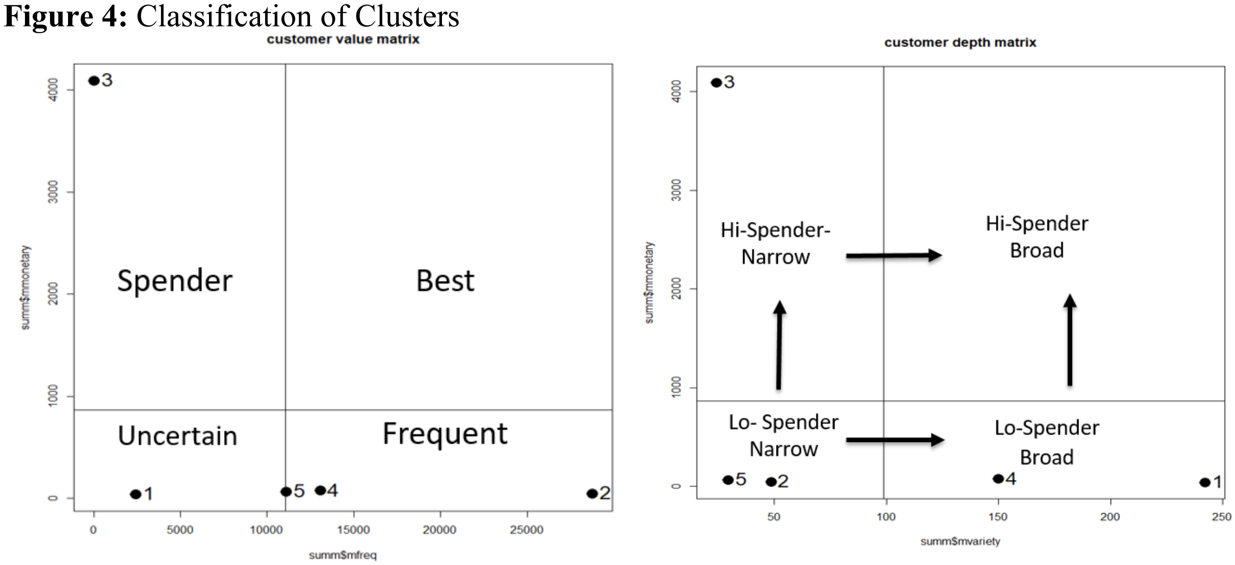
The number of customers and average RFM-V values for five clusters obtained are given in Table3. There are 2426 customers in the first cluster. Their recency averages are 178, their frequency averages are 2426, and their average expenditures are 242 TL. They bought 242 different products on average, which is the most variety among all clusters. There are 28776 customers in the second cluster. Their average recency is 160, and the average variety is 49. The most frequent customers are in this cluster. There are 13 customers in the third cluster. The most spending customers are in this cluster (M = 4093 TL). In the fourth cluster, there are customers who have the second most recency, frequency, monetary, and variety. The fifth cluster has mediocre values for all four variables.

Table 3: Cluster Statistics

Cluster	Count	Mean R	Mean F	Mean M	Mean V
1	2426	178	2426	40	242
2	28776	160	28776	47	49
3	13	114	13	4093	24
4	13063	172	13063	75	150
5	11104	60	11104	66	29

Based on these cluster statistics, the Customer Value Matrix and Customer-Product Depth Matrix are formed in Figure4. Cluster-based assessments are given in Table4. None of the clusters are in the best and hi-spender broad groups, which are the desired groups for the retailer. Hence, for all clusters, the retailer should plan activities to improve relationships with their customers to move them to top-right quadrants.

Figure 4: Classification of Clusters



Cluster #1 is in the uncertain and lo-spender narrow group. It can be named as growth potential customers. The retailer should up-sell to them to move them to the top-right (second) quadrant. Cluster #2 is in frequent and lo-spender narrow groups. This cluster can be named as thrifty customers because they come frequently but spend very little with low variety. The retailer should up-sell, and also cross-sell to them. Cluster #3 is in the hi-spender narrow group. They spend high amounts, but come seldom and buy low-variety products. This cluster can be named as the best customers. The relationship with these customers should be improved and the variety should be enriched. Cluster #4 has frequent and lo-spender broad customers. They come frequently, buy different variety, but spend low. They can be called potential customers. The retailer should up-sell to them. Cluster #5 is on the border of uncertain and frequent groups in the customer value matrix. They are also in the narrow group for variety, hence the most difficult to improve group is this one. They can also be called as thrifty customers. The retailer should both up-sell and cross-sell to them.

Table 4: Cluster-Based Assessments

Cluster	Value	Depth	Name	Action
1	Uncertain	Lo-Spender Broad	Growth Potential Customers	Improve&Up-selling
2	Frequent	Lo-Spender Broad	Thrifty Customers	Improve&Up-selling&Cross-Selling
3	Spender	Hi-Spender-Narrow	Best customers	Improve& Cross-selling
4	Frequent	Lo-Spender Broad	Potential Customers	Improve&Up-selling
5	Uncertain/ frequent	Lo-Spender Narrow	Thrifty Customers	Improve&Up-selling& Cross-Selling

The proposed RFM-V method and the customer-product depth matrix enable the retailer to focus on the depth of the customers and take actions to move customers to desired quadrants in the matrices.

Conclusion

RFM is an effective analysis method used by businesses to segment customers by examining the consumption behavior of customers within the scope of customer relationship management. Depending on the RFM value consisting of consumption range, frequency, and amount of money variables, customers can be divided into different groups and marketing strategies can be developed according to group information, profitable customer, one-time customer, uncertain customer, regular customer, etc. Such definitions can be made to ensure understanding the value of the customer in terms of the business. These definitions enable the company to identify customers who need to establish and develop their relationships. However, the RFM analysis cannot constitute a sufficient framework for the enterprise at the last stage, that is, at the stage of developing and deepening the relationship. In particular, the fact that important features such as the variety and quantity of the products purchased are out of the equation prevents the business from giving a healthy answer to the question of how it can improve its relationship with its customer.

Based on this basic problem, the researchers propose a modified RFM model that includes the variety of products purchased for use in customer segmentation. The number of product types purchased by the customer is added to the model as the V parameter. Thus, with the RFM-V analysis performed, businesses can categorize both their customers and the products they purchase with cluster analysis. It is predicted that this model will provide integration and productivity increase in marketing, sales, and supply chain functions, especially for businesses with a large number of product types such as supermarkets.

The researchers also proposed a model in which customer clusters can be analyzed based on quantity and diversity parameters with the "customer-market depth matrix" they created based on RFM-V analysis. According to this matrix, each customer cluster is located in one of four different quadrants. It is recommended to apply a different marketing and sales strategy to each cluster according to its region. Thanks to the V parameter added to the model, the deepening of the customer can be followed as well as the sales trend for purchased products. Analysis findings can be associated with basket analysis data in order to develop healthier marketing strategies and realize effective promotional suggestions.

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