Customer Loyalty Strategy Using Customer Lifetime Value (A Case Study of Jamu and Herbal Products SME)

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Abstract

Jamu is a traditional Indonesian medicine that has become part of the culture. The increasing demand for traditional medicines, especially *Jamu* in Indonesia due to the COVID-19 pandemic, provides opportunities for the traditional and herbal medicinal business. The increase in demand leads to the emergence of new traditional and health product SMEs, at the same time, online purchase transactions have also increased, encouraging SMEs to switch to e-commerce. This study aims to determine the segmentation and value of each customer segment using CLV and develop strategies for each customer segmentation in order to increase customer loyalty. The K-Means Clustering method is used to segment customers into several clusters and the CLV value is used to determine the value of each customer segment with Recency, Frequency, and Monetary (RFM) variables. Cluster deployment using the Customer Value Matrix (CVM) was also carried out to ensure cluster characteristics. Secondary data obtained from sales transactions. Analysis of product sales is carried out using the Association Rule method which produces one of the strategies in Customer Development. The research resulted in 5 clusters for customers with 13 strategies for the whole cluster. The cross-selling strategy is the recommended strategy.

Keywords
Customer Loyalty, Model RFM, Customer Lifetime Value, Herbal SMEs, Association Rules.

1. Introduction
Indonesians are one of the most enthusiastic users of digital technology in the world. A report by McKinsey & Company (2018) states that on average, Indonesians spent an hour a day to access the internet on their mobile devices, which is twice the average American. As of 2018, there are 30 million Indonesians who transact online, creating a market equivalent to 8 billion USD.

Bank Indonesia (BI) estimates the value of e-commerce transactions will reach 395 trillion Rupiah, or an annual growth of 48.4% in 2021. The value of e-commerce transactions in the first half of 2021 reached 186.75 trillion Rupiah or grew by 63.36% on an annual basis. SMEs are one of the most important economic sectors because they contribute greatly to Indonesia's GDP. In 2019, the contribution of SMEs to GDP reached 9.6 Quadrillion Rupiah. In May 2021, the total contribution of MSMEs reached 64.2 million Rupiah with a contribution to GDP of 61.06% or 8,573.89 trillion Rupiah.

With many SME players starting to register their stores on e-commerce platforms available in Indonesia, it is easier for customers to decide which products to buy. Every business actor, especially the *jamu* & herbal business, wants customers who continuously make purchases at their stores or who are often referred to as loyal customers. One way that SMEs can do to increase customer loyalty is to design a strategy that adapts to the preferences of their customers.

Jamu and Herbal business is also a business that requires loyalty from buyers because there is a very big opportunity to get customers who shop continuously in this business. Therefore, a Customer Relationship Management (CRM) strategy is needed that is in accordance with customer needs to increase customer loyalty. Customer segmentation is one of the most effective tactics to increase Customer Lifetime Value. The concept of Customer Lifetime Value (CLV) is part of Strategic Customer Relationship Management (CRM) which is widely used to predict the revenue that can be obtained from a customer by identifying its lifetime value. Dividing heterogeneous customers into segments will greatly help companies to carry out their marketing strategies. (Pater, 2019)states that customer segmentation is an effective method to satisfy customer needs and preferences. (Abbasimehr, 2019) also states that customer segmentation is an important CRM practice that enables businesses to achieve a deeper understanding of customer needs and behavior.

Jamu Sehat is one of the SMEs engaged in the *Jamu* and Herbal business. Jamu Sehat was founded in 2016 with 60 variations of products offered, ranging from herbs to cooking ingredients and other herbal products. Currently, Jamu Sehat products are available on various e-commerce platforms in Indonesia. In 2020, there were 14,551 customers with a repeat order percentage of 0.33%. The low percentage of repeat orders encourages Jamu Sehat to increase customer satisfaction and loyalty. To achieve this, customer segmentation analysis is needed to develop the best CRM strategy based on customer needs and preferences to increase customer loyalty.

1.1 Objectives

The aim of this study is to determine the level of customer loyalty in Jamu Sehat SME and to segment customers through the Recency, Frequency, and Monetary (RFM) model approach to determine customer segmentation, determine the value of each customer segment using Customer Lifetime Value (CLV) and develop strategies for each customer segment to increase customer loyalty for Jamu Sehat.

2. Literature Review

2.1 E-Commerce

Electronic commerce, or e-commerce, is the buying and selling of goods and services, as well as the movement of money and data, through an electronic network, most commonly the internet. Soliman & Janz (2004) defines the e-commerce as the electronic means of conducting business transactions and exchanging information within and outside the organization that enables the organization to quickly identify consumer needs and convey them to the entire supply chain. Another definition from Turban et al. (2015) regarding e-commerce is the process of purchasing, selling, or exchanging things, services, or information over the internet.

H. Zaied (2012) defined e-commerce is defined as a tool for facilitating the flow of commercial transactions over the internet, including the exchange of value information in the form of goods and services, as well as web-based payment transactions. Kotler & Armstrong defines e-commerce is defined as online channels that can be accessed via a computer and are used by businesses to carry out a variety of business activities, as well as by consumers to obtain information. The process begins with providing consumers with information services to assist them in making decisions.

Based on various definitions of e-commerce that have been described by experts, e-commerce is defined as online channels that can be accessed via a computer and are used by businesses to carry out a variety of business activities, as well as by consumers to obtain information. The process begins with providing consumers with information services to assist them in making decisions.

Turban et al. (2015) grouped e-commerce based on the relationship between actors into 5 types, namely Collaborative Commerce, Business to Consumer Commerce (B2C), Business to Business Commerce (B2B), Mobile-commerce, Customer to Customer Commerce (C2C).

2.2 Customer Relationship Management

CRM or Customer Relationship Management is a term that has been used since the early 1990s. There have been many attempts to define the term CRM. According to Don Peppers & Rogers, CRM stands for customer relationship management, and it is a technology or software solution that aids in the tracking of data and information about customers in order to improve customer service. In addition, CRM can also be interpreted as a set of business training plans, to bring companies closer to their customers, with the aim of learning more about them, one by one, and to provide better value so that each of them is more valuable as a customer. customer. CRM is also a method for businesses to better understand customer behavior through analysis and communication in order to increase customer acquisition, retention, and profitability. CRM was described by Dachyar & Hananto (2014) as a managerial activity for managing all customer interactions in a firm by combining business processes and technology to understand the customer as a whole.

CRM is divided into 3 types, namely Strategic, Operational, and Analytical. Strategic CRM refers to the core business strategy focuses on customers with the aim of winning and retaining customers that are considered profitable for the company. Sales, marketing, and customer service are just a few of the customer-related tasks that can be automated using Operational CRM. Analytical CRM is defined as The process by which an organization or company changes customer-related data to seek actionable insights for both strategic and tactical purposes.

According to Zeng et al., (2013), CRM has 4 characteristics, namely:
1) Relationship Management: Instant service response based on customer input, one-to-one solutions to customer needs, direct online communication with customers at any time and from any location, and a customer service center that can assist in the resolution of customer issues.
2) Automated salesforce execution: To realize salesforce, assess sales promotions automatically, manage customer accounts for repeat or future purchases, and coordinate sales, marketing, call centers, and retail outlets.
3) Technology Use: Adding value to the required data storage technology through the use of technology.
4) Opportunity Management : Manage unpredictable growth and demand using forecasting methods.

2.3 Customer Lifetime Value

A prior research defines CLV as the net profit or loss obtained by the company from the customer during the customer's transaction period at the company Jain & Singh (2002). S. Gupta & Lehmann (2003) defines CLV as the present value of all future benefits that can be generated from customers. Chang et al. (2012) defines CLV as a tool to measure how changes in customer behavior can affect the profits to be obtained by the company. Buttle & Maklan (2015) defines CLV as the present value of all net margins earned by the company from customer relationships and segments.

However, the underlying notion of Customer Lifetime Value (Bayón et al., 2002; Berger, 1998) focuses on the Net Present Value (NPV) obtained from the customer over the life of the transaction. Dwyer (1997) attempted to determine CLV by simulating client retention and migration. Using a tree-based and regression technique, (Hansotia & Rukstales, 2002) recommends value-added modeling for making investment marketing decisions. J. Hoekstra & Huizingh (1999) also proposes a conceptual CLV model and divides the model's input data into two categories: interaction data sources and time frames. Although we have many different CLV calculations with a variety of practical challenges, the majority of these CLV models are derived from basic equations. The basic model proposed is shown in Equation 1 to Equation 3.

$$CLV = \sum_{i=1}^{n} \frac{R - C}{(i + d)^i}$$

Equation 1. CLV Equation by **(Hoekstra & Huizingh, 1999)**

Equation 1 calculates CLV using Revenue from customers during period i customers (Ri), Cost of revenue earned during period i customers (Ci), interest rate (D), and number of desired customer lifetime value (n).

$$\mathbf{CLV = Historical\ Value - Potential\ Value}$$

Equation 2. CLV Equation by Hwang et al. (2004)

Equation 2 calculates CLV by subtracting historical value of a customer from potential value of a customer.

$$\mathbf{CLV = NRxR + NFxF + NMxM}$$

Equation 3. CLV Equation by Khajvand et al. (2011)

Equation 3 calculates CLV by adding up the normalized value of the RFM variable with the weights of each variable. The normalized value of the recency variable is multiplied by the weight of the recency variable then added to the normalized value of the frequency variable multiplied by the weight of the frequency variable then added to the normalized value of the monetary variable multiplied by the weight of the monetary variable. This study uses this equation to calculate the customer lifetime value.

3. Methods

3.1 RFM Model

When used to database marketing, the notion of RFM was proposed by Bult & Wansbeek (1995) and has proven to be quite effective by Robert C. Blattberg et al. (2008). The Recency (R), Frequency (F), and Monetary (M) measurements, which are three major purchase-related variables that influence the likelihood of a customer's future purchase, are used in RFM analysis..

The term "recency" refers to the amount of time that has passed since the most recent consuming behavior and the present. Many direct marketers believe that customers who have purchased recently are more inclined to buy again. Frequency refers to the number of transactions a consumer has made over a given period of time. This metric is based on the notion that customers who have made purchases are more inclined to acquire things than those who have not. The total amount of money spent by a particular consumer is referred to as monetary. To reduce frequency and monetary collinearity, (Marcus 1998) advises using the average total transactions rather than accumulating the total transactions.

The RFM attribute has values with different ranges. For this reason, this value needs to be normalized so that it has the same range, which is between 0 – 1. This value is normalized using the min-max normalization method (Khajvand et al., 2011). The equation is then shown in equation 4.
Where,

$$NV = \frac{V - Min}{Max - Min} New_{max} - New_{min} + New_{min}$$

Equation 4. RFM Variable Normalization

NV = Normal Value
V = Value
MaxA= Maximum value on attribute A
MinA= Minimum Value on attribute A

Several scholars have used RFM variables to create clustering models in recent years. In the value study of a clothes retailer's client database in Taiwan, (Wu et al. 2020) employed the RFM model and the K-Means technique to build strong links and eventually solidify client loyalty for high-profit long-term consumers.

RFM analysis is used to assess client loyalty and, as a result, cluster analysis is used to discover target consumers with high RFM values. The ability to use multiple marketing methods for different consumer segments is the key benefit of this process. Furthermore, segmenting clients into different categories increases the quality of recommendations and assists decision-makers in identifying clearer market segments and developing more successful strategies.

3.2 Pairwise Comparisons

The pairwise comparison technique, also known as the pairwise comparisons matrix, is widely used in multi-criteria decision making (MCDM) to deal with subjective and objective judgments about qualitative and quantitative criteria, particularly in the Analytical Hierarchy Process (AHP) and Analytical Network Process (ANP) (PCM). Decision makers' judgment fills in preference connections in PCM, which are displayed using a variety of measurement scales, including ratio scales (Saaty 1977), geometric scales (Lootsma 1989), and logarithmic scales (Ishizaka et al. 2010).

Preference is determined by the results of paired comparisons, in which criteria are rated on a one-to-nine intensity-importance scale. Following the decision maker's evaluation of the criteria on the above-mentioned scale, a comparison matrix is created, which includes paired comparisons of all distinct alternatives or criteria (Dachyar et al. 2019).

3.3 K-Means Clustering

The K-Means method is used in segmenting an object from a research. This method was first introduced by Tyron in 1939. There are several different algorithms that can be used in performing clustering techniques, one of which is the K-Means method. This method itself is quite efficient even though it has to use many experiments (Pang-Ning, Steinbach, & Kumar, 2006). In this method, the number of clusters is determined by the decision maker. K-Means itself is limited by data that has a centroid.

When using K-Means, the researcher must first establish the number of starting clusters, after which the centroid in each cluster must be calculated. We allocate the data to the centroid with the closest distance after calculating the centroid in each cluster, and then recalculate the new centroid until no data moves clusters.

To be able to determine the nearest centroid cluster, one of them is to use the Euclidean Distance method with the equation 2 :

$$D = \sum_{j=1}^{p} (Xij - Xhj)^2$$

Equation 5. Euclidean Distance Calculation

where,

D = Euclidean square distance between objects
P = Number of cluster variables
Xij = Value or data of object i in variable j
Xhj = Value or data from object h in variable j

3.4 Association Rules

Association rules refer to statistical methods in the database of trade transactions from product category X on purchases from goods category Y, which shows the tendency of buyers to buy other goods when buying goods that they really want. Many firms can benefit from the finding of associations of interest in a large number of business transactions, such as catalog design, cross-marketing/cross-selling, and loss-leader analysis (Sumathi & Esakkirajan, 2007). Customers with the same RFM value and demographic factors buy in similar ways, as evidenced by the pattern of transactions (Birant 2011).

The study of "what with what" is the focus of association rules or affinity analysis. Some examples can be found in supermarket transaction research, such as when a person buys soap and also buys toothpaste at the same time. Because association rules are employed in processing customer transaction databases to determine customer buying behaviors for a product category, they are also known as market basket analysis. The information should be provided in the form of a "if-then" relationship, according to association guidelines. This rule is based on probabilistic information.

There are 3 principles regarding Association Rules which are a) Support, b) Confidence, c) Lift. Support refers to the frequency of item a or the combination of item a and b which basically is the frequency of the items that has been bought together. Confidence shows how often item a and b occur together given the number of times a occur. Lift provides the independent occurrence probability of a and b. Below are the equations for each principal Equation 6 is used to calculate association rules principles.

$$Support = \frac{Freq\ (A,B)}{N} \qquad Confidence = \frac{freq(A,B)}{freq(A)} \qquad Lift = \frac{Support}{Supp(A)\ x\ Supp(B)}$$

Equation 6. Association Rules Principal Calculation

3.5 Business Intelligence

Business Intelligence (BI) is a set of tools, techniques, and processes that help companies maximize existing data into various forms to gain knowledge and make better decisions based on facts (Jennex & Bartczak 2013). BI itself provides an opportunity for companies to be able to use existing data as well as possible, both structured data such as relational databases and unstructured data such as web logs. When the data has not been processed, the data cannot identify useful facts. Therefore, it is necessary to process data in order to produce useful data.

The application of BI in CRM can generate some value to the company. BI Values consist of 5 values, namely Customer Values, Financial Values, Technical Values, Employee Values, and Business Process Values. Phan & Vogel (2010) suggests that Customer Satisfaction is part of BI values in CRM. This was proven by a research by Tsai et al. (2015) describes BI values in CRM including Customer Satisfaction Customer Loyalty, Customer Retention, Better Corporate Finance, Real time Analysis, Employee Motivation, and Employee Satisfaction. Another research by

Handzic (2015) suggests that Efficiency and Effectiveness Increase is also a part of BI values in CRM. This is then proved by another research that suggests Efficiency and Effectiveness Increase is also a part of BI values in CRM.

4. Data Collection

The data used in this study is secondary data from *Jamu* and Herbal SME who sell their products through e-commerce platforms available in Indonesia. The data used is purchase history data from August 1, 2020 until August 1, 2021. Researcher also collect and process primary data in the form of opinions from experts to weight the RFM variable. The author uses Spotfire Analytics software to extract RFM variables. The extraction process will generate RFM variable values for each customer. Primary data collection was carried out in the form of opinions from experts regarding the weighting of the RFM variables. Expert opinions were obtained through interviews and questionnaire tools which contained pairwise comparisons of the three RFM variables. The following is a summary of the transaction data obtained on table 1 as well as the product data on table 2.

Table 1. Transaction History Data Summary

Data Type	Summary
Transaction	26649 transaction
Transaction in Rupiah	$390,000
Customers	15786 customers
First Transaction Date	01 August 2020
Last Transaction Date	01 August 2021

Table 2. Product Category Data Summary

Product Category	Quantity
Jamu (Coded as J)	40
Herbal / Pure Ingredients (Coded as B)	14
Other Products (Coded as L)	6

5. Results and Discussion

In this study, the steps taken in data processing to calculate the Customer Lifetime Value (CLV) and the Association Rule strategy carried out for Customer Development in order to retain customers are as follows,
1) Extract the RFM variable based on sales transaction data using Spotfire Analytics, 2) Perform customer segmentation with customer segmentation using the K-Means Clustering method, 3) Calculate customer CLV using RFM variable weights obtained from experts, 4) Create a strategy for each customer group, 5) Create a Customer Development strategy using product data through the Association Rules approach.

5.1 Numerical Results

1) RFM Extraction

Recency is the time interval from the last transaction to the end of the research time. Frequency is the number of transactions made by a customer during the study period. Monetary is the total money that customers spend on transactions during the study period. The following table 3 to 5 shows the distribution of the three variables.

Table 3. Recency Distribution

Recency (Days)	Customers
< 73	5558
73 – 146	2844
147 – 219	2594
220 – 292	2087
≥ 292	2655

Based on table 4, the most number of customer recently purchased their order from the SME. It is shown by 5558 customers that purchased below 73 days from the end of the research period.

Table 4. Frequency Distribution

Frequency	Customers
1 – 2	13491
3 – 4	1485
5 – 6	470
7 – 8	168
9 – 25	172

Based on table 5, customers rarely shop repeatedly from the SME. It is shown by 13491 customers that purchased 1-2 times throughout the research period.

Table 5. Monetary Distribution

Monetary	Customers
< \$34.83	12863
\$34.83 - \$69.68	1978
\$69.68 – \$209.03	863
\$209.03 – \$3483.90	69
≥ \$3483.90	13

From table 7, customers tend to purchase less than \$34.83 as it has 12863 customers. The RFM variable scale is needed to be the basis for segmenting customers in the next stage. The customer analysis process with the most famous RFM model is to use the quintile method (Wei, Lin, & Wu, 2010) where this method wil divide the range of RFM variables that have been extracted equally.

The RFM parameter will be shown below on table 6 where this will be used to facilitate the analysis of each segment after establishing an equal division.

Table 6. RFM Parameter Scale

Score	*Recency* (Days)	*Frequency*	*Monetary*
5	*< 73*	9 – 25	≥ \$3483.90
4	*73 – 146*	7 – 8	\$209.03 – \$3483.90
3	*147 – 219*	5 – 6	\$69.68 – \$209.03
2	*220 – 292*	3 – 4	\$34.83 - \$69.68
1	*≥ 293*	1 – 2	< \$34.83

Based on table 7, it can be concluded that a small number of days shows a large value for the recency variable, for a high frequency value itself indicates high loyalty in terms of purchase intensity, and a higher monetary value indicates greater loyalty in terms of the nominal purchase amount.

2) Pairwise Comparisons

The experts were consulted after the surveys were distributed to determine the weights and priority. The combined expert weights were then calculated using the Experts' Choice software. Each respondent's response to the AHP pairwise comparison needs to have inconsistency below 0.1 to ensure that the respondent's feedback is consistent and reliable (Nurcahyo et al., 2018). Table 7 shows the weight of the RFM variable based on experts assessment.

Table 7. RFM Variable Weight

Variable	Weight
Recency	0.075
Frequency	0.592
Monetary	0.333
Total	1

3) K-Means Clustering

The number of clusters tested in this study ranged from 3 clusters to 5 clusters, based on the literature that has the appropriateness of the object in this study. Clustering with K-Means is done with the help of Spotfire Analytics software. The Euclidean Distances method is used as the basis for clustering data with existing RFM attributes. This method will produce clusters with a maximum distance between clusters and a minimum distance between members in the cluster (Zhu et al., 2011). The RFM attribute data for each customer is used as input for processing this data in the Spotfire Analytics software. Table 8 shows the average values of RFM attribute for each cluster.

Table 8. Average Values of RFM Attribute for each cluster

K-Means Cluster	Average (Recency)	Average (Frequency)	Average (Monetary)
1	165	1	$11.53
2	125	2	$35.67
3	85	4	$77.06
4	57	7	$151.68
5	45	11	$303.57

Following the determination of the cluster range, the cluster (k) must be searched for the most optimal value. One of the ways to determine the optimal value of k is by using the cross-validation method. The use of cross-validation is to run M partitions to be tested from a set of D data. This approach is also better in determining the number of clusters from a data set based on the smallest training error value (Halkidi, 2001). Table 9 shows the value of training error for k=3,4,5.

Table 9. Training error for different value of k

Number of Cluster	Training Error
3 clusters	0,123613
4 clusters	0,095957
5 clusters	0,076516

When looking at the training error values in each cluster, as shown in table 9, it is clear that the cluster with k = 5 has the minimum training error value. The cluster with k = 5 has the smallest training error value, which is 0.076516, or approximately 76.5 percent. This cluster will represent the segmentation of existing customers. The table below shows the average values of the RFM attribute for each cluster.

4) Customer Lifetime Value

The formula used to calculate the CLV value is the equation used by (Khajvand et al., 2011), the CLV value can be calculated by calculating the RFM normal value along with the weight of each RFM attribute obtained from the respondent's assessment. Table 10 shows the result of the RFM Normalization calculation.

Table 10. Normalization Value for RFM Attribute with k=5

Cluster	R	F	M	NR	NF	NM
1	165	1	$11.53	0,45055	0	0,01976
2	125	2	$35.67	0,34066	0,04167	0,06113
3	85	4	$77.06	0,23077	0,12500	0,13209

Cluster	R	F	M	NR	NF	NM
4	57	7	$151.68	0,25385	0,25000	0,25999
5	45	11	$303.57	0,12088	0,41667	0,52031

The weight of the RFM attribute according to the expert's assessment shows that the frequency attribute has the largest weight, followed by the monetary attribute and the recency attribute, which means that this frequency has the greatest importance in assessing customers at *Jamu* and Herbal SME. By using the weights in table 8, the CLV value can be calculated using the normalized value of the RFM attribute that has been obtained previously. The following table 11 is the result of the CLV calculation.

Table 11. CLV Calculation for each Cluster

Cluster	NR	R	NF	F	NM	M	CLV	CLV Rank
1	0,450549	0,075	0	0,592	0,019755	0,333	0,04037	5
2	0,340659		0,041667		0,061131		0,07057	4
3	0,230769		0,125		0,132085		0,13529	3
4	0,153846		0,25		0,259988		0,24611	2
5	0,120879		0,416667		0,520315		0,42900	1

Authors then determines the RFM Characteristic of each cluster after computing the customer lifetime value (CLV).Table 14 shows that cluster 4 and cluster 5 are the two clusters with the highest CLV value with a fairly substantial value between the two, namely 0.25 to 0.43. Based on the RFM characteristics possessed by the two clusters, it can be said that they belong to a cluster with the Best / Valuable Customer category which can also be interpreted as a cluster with loyal customers. Cluster 3 has the characteristics of customers who are just in the early stages of purchasing at this store because they have a combination of RFM R↑F↓M↓ and are included in the First Time Customer category. Clusters 1 and 2 are the clusters with the last rank where these two clusters have the lowest value for CLV. This category is called Uncertain Customer.

Table 12. CLV Calculation Combination and RFM Characteristic

Cluster	Customers	CLV Rank	RFM Combination	Customer Characteristic
1	11181	5	R↓F↓M↓	*Uncertain Customer*
2	3246	4	R↓F↓M↓	*Uncertain Customer*
3	980	3	R↑F↓M↓	*First Timer Customer*
4	313	2	R↑F↑M↑	*Best / Valuable Customer*
5	66	1	R↑F↑M↑	*Best / Valuable Customer*

5) Customer Value Matrix

Segment mapping based on CVM is needed because there are still shortcomings in the segmentation results using the K-Means method only. Mapping with this matrix is used effectively to be able to help to understand more deeply the results of segmentation as a basis for making a decision (Marcus 1998).

The Customer Value Matrix uses the average value of the frequency and monetary attributes of each cluster as a separator between the quadrants formed. The average of the amount of money spent by customers (monetary) is used to obtain the Y axis. The average of the number of purchases made by customers (frequency). Because in this study clusters are used as objects to be mapped, the total frequency and monetary attributes can be divided by the total number of existing clusters, which is 5 clusters. Table 13 shows the average values used as a dividing line (axis) between quadrants.

Table 13. Average CVM Axis

X Axis	Total frequency from 5 clusters	25
	Frequency average value	5
Y Axis	Total monetary from 5 clusters	Rp8.316.892
	Monetary average value	Rp1.663.378,40

Table 14 divide the cluster based on their CLV to their respective quadrant using the established CVM axis. Customers are divided into 2 characteristics, Best and Uncertain. Best consists of 379 customer coming from cluster 5 and 4. Uncertain consists of 15407 customers coming from cluster 1, 2, and 3.

Table 14. Description of CVM Mapping

Quadrant	Cluster	Characteristic	Customers
Quadrant 1	Cluster 5	*Best*	379
	Cluster 4		
Quadrant 2	-	*Spender*	-
Quadrant 3	Cluster 1	*Uncertain*	15407
	Cluster 2		
	Cluster 3		
Quadrant 4	-	*Frequent*	-

6) Association Rules

STATISTICA is used to calculate the data. The result generates 176 combinations of association rules with confidence and support values 0.1%. The results, 176 combinations, are still too many if used as recommendations for SME as product bundling.

According to (Larose, 2008), researchers are free to determine the minimum support and confidence values according to our needs. To be able to eliminate several rules that have low support and confidence values, the authors increase the minimum support and confidence values gradually until the support and confidence values reach 5%. The results obtained are 4 combinations of association rules that can be recommended to SME as shown on table 17.

Table 15. Summary of Association Rules with 5% Confidence and Support Value

No	**Body**	**==>**	**Head**	**Support(%)**	**Confidence(%)**
1	B5	==>	B7	9.27820	79.64377
2	B7	==>	B6	6.78820	28.16728
3	J5	==>	J3	11.51623	55.61918
4	J1	==>	J3	9.30784	69.62306

5.2 Graphical Results

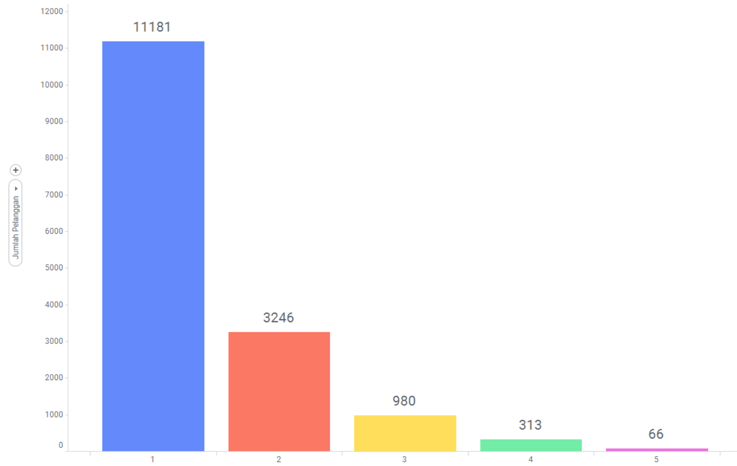

Figure 1. Distribution of Customer in Each Cluster

Based on segmentation using the k-means method in figure 1, SME Jamu and Herbal customers are divided into 5 clusters. The cluster that has the most number of members is cluster 1, which has 11181 customers. This is because, many customers are in accordance with the characteristics of RFM as in the cluster. This is then used to be the baseline to calculate the CLV.

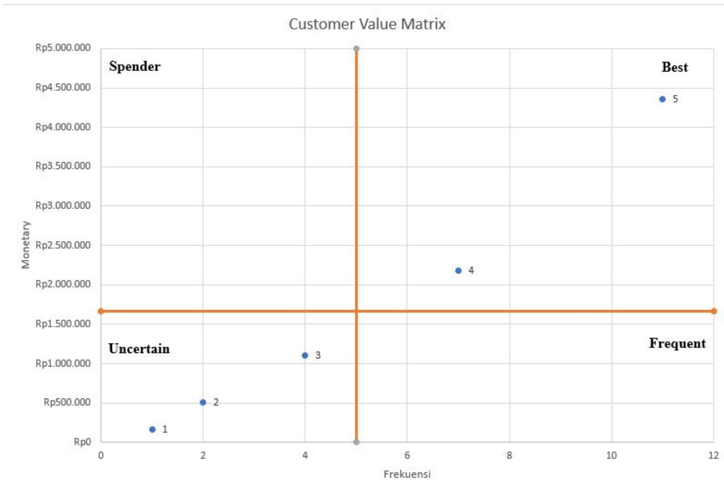

Figure 2. Customer Value Matrix Mapping

The CLV is then utilized to map the customer utilizing the customer value matrix after computing the CLV and matching their characteristic to their relevant cluster. Based on the figure above, the customer is divided into 2 characteristics which is Best for cluster 5 and 4 and Uncertain for cluster 3,2, and 1.

5.3 Proposed Improvements

A research by Dachyar et al. (2019) suggests that companies need approachment methods to enhance customer loyalty from potentially useful, ordinary, and perhaps invaluable consumers. Of all the clusters, cluster 5 and 4 are rated as the clusters that have the highest and best loyalty to the company. Because this cluster is filled with loyal customers, the results of this cluster analysis using the RFM and CVM methods show that this cluster is included in the category of Best / Valuable Customer based on RFM and Best Customer based on CVM. Therefore, companies need to keep customers in this cluster. These two clusters themselves are considered very valuable for the company and because of their small number of 379 customers.

SME need to implement some strategies in order to maintain as well as increase their loyalty. Making cross-selling with a discount is one of the most recommended strategy as it is one of the easiest to implement without the need of having excess cost unlike when recruiting customer service or even adopting new technology. Cross-selling combination has been obtained using association rules. Those combination include 4 combination of products to be sold together. B5 (Yellow spices) and B7 (White spices), B6 (Red spices) and B7 (White spices) , J5 (Immunity boosting *Jamu* for Kids) and J3 (Immunity boosting *Jamu* for Adults), J1 (Vitamin E rich *Jamu)* and J3 (Immunity boosting *Jamu* for Adults).

6. Conclusion

To determine the customer loyalty of *Jamu* & Herbal SME, 15786 customers were divided into 5 clusters, where the fifth cluster is the most loyal cluster with a CLV value of 0.43 and the first cluster being the least loyal with a CLV of 0.04. The results of the Customer Value Matrix analysis show that clusters 4 and 5 are included in the best customer category because they have high Recency, Frequency, and Monetary values, which are above the average frequency and monetary clusters. From the 13 recommended strategies, the cross-selling strategy with discounted prices is the easiest strategy to implement to increase and maintain customer loyalty.

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