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B2B Customer Segmentation Based on Customer Lifetime Value Concept and RFM Modeling

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Abstract:

The company has limited resources to use in implementing marketing strategies for its customers. The first step to be able to develop an effective and efficient marketing strategy is to divide customers into several large groups based on their similarities. The company needs to allocate its limited resources proportionally to groups of customers based on the value and benefits that those customers can contribute to the company. One of the bases for customer grouping is based on the concept of Customer Lifetime Value (CLV) with Recency, Frequency, and Monetary (RFM) modeling. CLV ratings show how much value and benefits customers can bring to a company. This study conducted a cluster analysis with the K-means algorithm on 351 customers based on their RFM value. The number of clusters is most effectively obtained through the elbow method. Cluster analysis produces 4 customer clusters that have different characteristics and are ranked based on their CLV values. Cluster names and marketing strategy recommendations for each cluster are arranged based on their characteristics and CLV rating. The four clusters formed are the Non-Valuable Customers cluster, VIP Customers cluster, Valuable Customers cluster, and Potentially Valuable Customers cluster.

***Keywords**: RFM, Customer Lifetime Value, K-means Clustering*

1. Introduction

Many companies still use traditional methods to segment customers. According to Pratomo et al. (2019), the policy can result in ineffective marketing strategies and consume resources owned by the company. As a profit-oriented organization, the company must know the value or benefits that each customer can provide and allocate limited resources proportionally (Cuadros and Domínguez, 2014). Therefore, it is natural for companies to apply customer segmentation based on their value and benefits.

Many companies measure the value of their customers based on their level of loyalty. According to Kumar and Rajan (2009), loyal customers do not necessarily provide benefits to the company. Similarly, the commitment and level of customer trust. Both variables can show the difference between active and passive customers but cannot

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directly display how much these customers can provide benefits or value to the company now and in the future (Hultén, 2007). The value and benefits that can be provided by customers to the company can be shown by the Customer Lifetime Value (CLV). CLV describes the net present value of the stream of future profits expected over the customer's lifetime purchases (Kotler and Keller, 2016). This shows that CLV can inform the present value of the customers and their potential value in the future (Khajvand and Tarokh, 2011).

Several models can be used to calculate a customer's CLV. One of the most powerful and easy-to-implement models for estimating customer value is to use of RFM models – Recency, Frequency, and Monetary (Gupta et al., 2006). According to McCarty and Hastak, (2007), the RFM model may be the most powerful and simplest technique for generating knowledge from CRM data. RFM value analysis can help companies group customers so that they can distinguish which customers are the most valuable and which are not based on when they last made a purchase (R), how often they made purchases (F), and what the total value of transactions that have been made (M). In addition, RFM analysis can also be used to identify profit-generating customers, and determine the development of new products and services in finance, telecommunications, e-commerce, and many other fields (Wei et al., 2010; Khajvand and Tarokh, 2011; Hu and Yeh, 2014; Wong and Wei, 2018). Despite some drawbacks, some studies still suggest the use of RFM models arguing that past consumer purchases are a better predictor of future buying behavior (Gupta et al., 2006).

PT. SI is the sole agency holder Indonesian company of a brand of engineering products. The company supplies its products and services to customers from various industrial segments, such as energy, manufacturing, and mining. Headquartered in Jakarta, PT. SI serves customers from all regions of Indonesia in B2B business. PT. SI has also used Enterprise Resource Planning (ERP) software in carrying out its business processes so that customer data, customer transactions, and other important information can be obtained easily.

Based on an initial interview with PT. SI, companies group customers based on their industry type. The company gives more service and priority to customers who made large purchases in the previous year. In addition, companies also rely heavily on the experience and instincts of their marketers in developing marketing strategies. This certainly shows that the company still applies traditional methods and does not consider other variables or other customer attributes in segmentation.

This research was conducted to group customers owned by PT. SI based on CLV concept using RFM modeling. From this process, several large groups of customers who have unique profiles and CLV values will be obtained. The CLV of each customer group is determined by the weight of RFM variables obtained through the Analytical Hierarchy Process (AHP) method involving representatives of decision-makers in the company (Ray and Mangaraj, 2016). By considering the profile and CLV rating, recommendations for effective and efficient marketing strategies can be prepared for each customer group.

2. Theoretical Background

Customer Segmentation
Kotler and Keller (2016) state that market segmentation is the process of dividing a market into well-defined pieces. A market segment consists of a set of customers who share the same needs and interests. A marketer has the task of identifying the number of segments, understanding the nature of the market segment, and deciding on it as a target.

Research shows that customer segmentation can be done based on a wide variety of parameters (Paul and Ramanan, 2019). Especially now that many companies have applied the concept of data mining to run Customer Relationship Management (CRM) (Imani et al., 2022). Customer data obtained from daily operational activities can be transformed into useful knowledge for the company (Dursun and Caber, 2016). Customer databases can be used to segment customers determine target customers, win competition, and maintain customer loyalty (Buttle and Maklan, 2019).

Various algorithms can be used for customer cluster analysis. One of the most popular is the K-means algorithm (Sheikh et al., 2019). The purpose of using the K-means algorithm is to group data by maximizing data equations within one cluster and minimizing data equations between clusters (Pratomo et al., 2019). The K-means algorithm is widely used to identify valuable customer groups as well as develop marketing strategies (Mesforoush and Tarokh, 2013).

Customer Lifetime Value and RFM Analysis
Gupta et al (2006) describe several models that can be used in estimating customer CLV value. These modeling include RFM modeling, Probability, Econometric, Persistence, Computer Science, and Diffusion / Growth. All of these models utilize customers's transaction data recorded by the company.

RFM modeling is a powerful and recognized technique in database marketing (Christy et al., 2021). Recency (R) is the time interval between the date of the last purchase and the last date of the statistical period. The smaller the value of the time interval, the higher the value of R (Imani et al., 2022). Frequency (F) indicates the number of times a customer purchased during the statistical period. The higher the F value, the more loyal the customer is to the Company (Christy et al., 2021). Monetary (M) is the total value of transactions that have been made by customers during the statistical period. The greater the value of M, the greater the revenue contributed to the company (Christy et al., 2021) and the intention to buy more (Dursun and Caber, 2016). Through RFM analysis, companies can extract customer profiles based on multiple criteria and reduce the complexity of the analysis process. CLV values can also be obtained through RFM modeling with simple equations (Qadadeh and Abdallah, 2018).

Wu et al (2020) group customers from an online shopping platform based on the value of RFM variables as an indicator of purchase behavior. The K-means algorithm is used to perform cluster analysis. The results of the analysis show the formation of 4 customer segments that have different RFM behavior characteristics. A similar method was also carried out by Husein et al (2021) on online shopping customer transaction data. The only difference lies in the software used to run the K-means algorithm.

Some other studies add other variables to RFM modeling to perform cluster analysis. Demographic variables such as age, gender, and country are involved in the RFM-based cluster analysis (Takci, 2016). The addition of demographic variables can help the process of analyzing the profile and character of customer clusters as well as formulating marketing strategies for each cluster formed (Dursun and Caber, 2016). Firstly, RFM variable weighting is performed to get the customer's CLV value. The weighting will determine which variable is more important than the other variables (Liu and Shih, 2005). The weight of each RFM variable is highly dependent on the type of company industry and decision makers of a company (Monalisa et al., 2019). Therefore, the AHP method is used by involving representatives of decision-makers in the Company (Safari et al., 2016).

Analysis of the RFM value and CLV rating of each cluster can help management in determining marketing strategy (Paul and Ramanan, 2019). Dogan et al. (2018) provided a better customer segmentation method using the RFM variable for retail store chains in Turkey. Customers were divided into four clusters. Dachyar et al. (2019) managed to divide the customers of a fashion brand into 5 groups and named them based on their CLV rating. Several marketing strategies are recommended to keep customers in the potentially valuable, average, and potentially invaluable groups. Son et al. (2020) recommend up-selling marketing strategies for the Best cluster, cross-selling for the Frequency cluster, product education for the Spender cluster, and product trial for the Uncertain cluster.

3. Methodology

This research was conducted in several steps as illustrated in the flowchart Figure (1). The flowchart is prepared by adopting methods derived from several previous studies that have been mentioned in literature reviews. Broadly speaking, these steps can be divided into 3 main phases, namely the data preparation phase, the data processing and analysis phase, and the marketing strategy preparation phase.

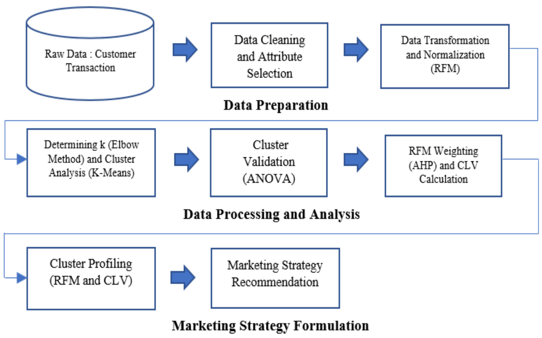

Figure 1. Proposed Research Process

Data Preparation
This research uses quantitative secondary data in the form of customer transaction data from PT. SI during the period January to December 2022. The data came from 351 customers, which in this study can be referred to as the population, obtained by downloading from the company's ERP system. Customer transaction data contains various information such as customer name, customer address, customer industry segment, order number, order date, order value, and various other information.

To be analyzed further, customer transaction data needs to be cleaned from duplication and error data and then transformed into RFM datasets (Wu et al., 2020). The R-value has units of days and can be obtained by subtracting the end date of the statistical period from the date of the customer's last order. The F value has no units and can be obtained by looking at the number of orders held by the customer during the statistical period. The value of M has USD units and can be obtained by adding up all the values of orders placed by customers during the statistical period.

Due to the significant difference in the range of values among RFM variables, min–max normalization is required to standardize dataset values (Safari et al., 2016). It aims to eliminate the impact of numerical values in the segmentation process (Wu et al., 2020).

$$x'_{ij} = \frac{x_{ij} - \min x_j}{\max x_j - \min x_j}$$

Where :
x'_{ij} : Normalized variabel i-th
x_{ij} : Variable i-th
$\min x_j$: Minimum value of variabel
$\max x_j$: Maximum value of variabel

A standardized RFM dataset will have the same range of values and no longer have units.

Data Processing and Analysis
After each customer's RFM dataset is complete, the next process that must be done is to group the customer data into several large groups using the K-Means algorithm with the help of the SPSS 24 program. The K-means algorithm can be done through 5 steps (Dachyar et al., 2019). The first step is to determine the number of clusters or K value. The second step is to randomly determine the initial centroid point or number of k values. The third step is for each data point to gather with the nearest centroid point and then form a group. The fourth step is to recalculate the centroid point. The final step is to repeat steps 2 – 4 until termination. To determine the most optimal number of k, the elbow method technique is used based on the Within Cluster Sum of Square (WCSS) value (Raiter, 2021).

$$WCSS = \sum_{i=1}^{n} d_i^2$$

Where :
$WCSS$: Within Cluster Sum of Square
n : Number of clusters
d : Distance between sample and centroid

Clusters formed through the K-means algorithm can be validated using ANOVA analysis (Sutarso et al., 2022). This is done to prove that the value of the RFM variable between the clusters formed is significantly different.

The next step is to calculate the CLV of the customer cluster. The CLV of each customer cluster can be obtained through equation (3) (Safari et al., 2016).

$$C_j = W_R C_R^j + W_F C_F^j + W_M C_M^j$$

Where :
Cj : CLV of the customers
W_R : Recency relative weight
C_R^j : Recency value of the customers
W_F : Frequency relative weight
C_F^j : Frequency value of the customers
W_M : Monetary relative weight
C_M^j : Monetary value of the customers

The weight of the RFM variable is obtained through the AHP method. Here are some steps to execute the AHP method. The first step is a pairwise comparison of RFM variables by distributing questionnaires, illustrated in Table 1, to decision-making representatives (Liu and Shih, 2005). Representative of PT. SI consists of 1 General Manager in Sales &; Marketing and 3 Sales Managers. The second step is to assess the consistency of the answers to the pairwise comparison questionnaire results (Dachyar et al., 2019). The Consistency Ratio (CR) value can be calculated using equation (4). The final step is to calculate the relative weight of the RFM variable using eigenvalue (Dachyar et al., 2019).

$$CR = \frac{(\lambda_{max} - n)/(n-1)}{RI}$$

Where :
CR : Consistency Ratio
λ_{max} : Maximum eigenvalue
n : Matrix order
RI : Random consistency index

Marketing Strategy Formulation

Marketing strategies are prepared based on the RFM variable character of the customer cluster and its CLV rating (Paul and Ramanan, 2019). The characters of RFM variables are indicated by up and down arrow symbols. The downward arrow symbol (↓) means that the value of the RFM variable is lower than the population average value. While the upward arrow symbol (↑) means that the value of the RFM variable is higher than the average value of the population (Dursun and Caber, 2016).

The CLV rating of each customer cluster is sorted based on the integrated rating value obtained from equation (3).

4. Empirical Findings/Result

Respondent Characteristics
Various kinds of information related to customers can be obtained through downloaded transaction data. Information related to customer characteristics or demographics can be combined with RFM analysis for marketing strategy development (Takci, 2016). The first demographic attribute we use is customer location. Information related to the location of PT. SI customers can be seen in Figure (2).

Table 1. Comparison Pairwise Questionnaire

Variable	**Comparative Importance**									**Variable**
	9:1	**7:1**	**5:1**	**3:1**	**1:1**	**1:3**	**1:5**	**1:7**	**1:9**	
Recency										Recency
Frequency										Frequency
Monetary										Monetary

Source: Liu Shih (2005)

Based on the Figure (2), 39.03% of PT. SI customers are located in DKI Jakarta province. East Java and West Java provinces have the second largest customers with a percentage of 11.68%. The majority of customers of PT. SI is centralized on the island of Java while customers with overseas addresses have a percentage of 4.27%. Overseas customers are mainly located in Singapore. In addition to location, customer characteristics of PT. SI can also be seen from its industry segment. Figure (3) shows the distribution of customer industry segments.

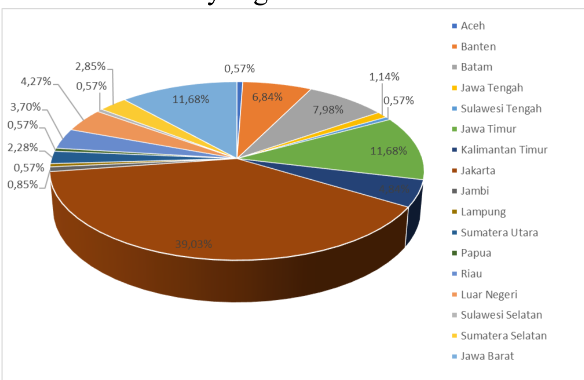

Figure 2. Customer Location Chart
Source : Processed Data (2023)

PT. SI customers is dominated by the Oil and Gas industry segment with a percentage of 59%. The second largest industrial segment is Chemical & Refinery with a percentage of 13%. Other industrial segments, such as Power, Pulp &; Paper, F&B, Transportation, and Mining complement the customer characteristics of PT. SI with a percentage below 10%. Oil and Gas industry segment is PT. SI main segment since the company's establishment.

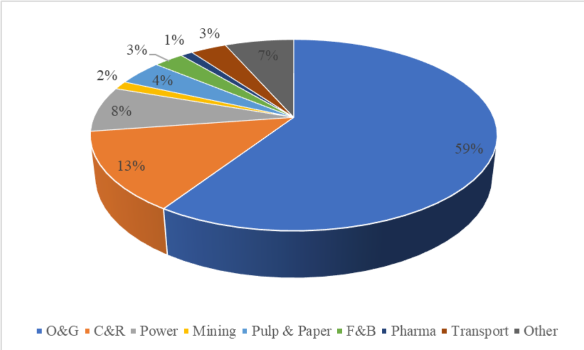

Figure 3. Customer Industry Segment Chart
Source : Processed Data (2023)

Customer Dataset

The main process in the data preparation phase is transforming the customer transaction data of PT. SI into RFM dataset. From the transaction data made by 351 customers in the 2022 period, the initial dataset is obtained as shown in Table (2).

Table 2. Initial RFM Dataset

Customer Name	Recency (Day)	Frequency	Monetary (USD)
Customer 1	339	2	17,661.20
Customer 2	54	1	489.83
Customer 3	17	19	47,171.43
Customer 4	26	20	25780.79
…..	…..	…..	…..
Customer 351	2	6	43,668.96

Source: Processed Data (2023)

The process of standardizing RFM datasets uses the min-max normalization method indicated by the equation (1). The normalization results can be seen in Table (3). The RFM dataset of the customers in Table (3) is ready for the cluster analysis process using the K-means algorithm.

Table 3. Normalized RFM Dataset

Customer Name	Recency	Frequency	Monetary
Customer 1	0.061	0.007	0.010
Customer 2	0.853	0.000	0.000
Customer 3	0.956	0.125	0.027
Customer 4	0.931	0.132	0.015
…..	…..	…..	…..
Customer 351	0.997	0.035	0.025

Source: Processed Data (2023)

Cluster Analysis

Cluster analysis is performed using the K-means algorithm. Dachyar et al (2019) mentioned that the initial step of the K-means algorithm is to determine the number of clusters or k value. Determination of k value using elbow method.

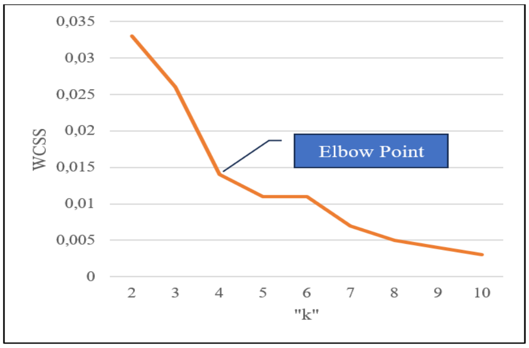

Figure 4. WCSS vs k Graph

Source : Processed Data (2023)

Figure (4) is a two-dimensional graph that shows the relationship between k values and Within Cluster Sum of Square (WCSS) values. Based on Figure (4), the value of k, or the number of clusters, is most optimal for the K-means algorithm in this study is as many as 4. This is indicated by the elbow point in the graph below. A significant decrease in WCSS value occurs until the k value is 4 and begins to slope for a larger k value.

Table 4. Customer Cluster and RFM Score

Cluster	N	R	F	M	Score
Cluster 1	83	0.193	0.002	0.002	R↓F↓M↓
Cluster 2	1	0.997	1.000	1.000	R↑F↑M↑
Cluster 3	149	0.904	0.060	0.019	R↑F↑M↑
Cluster 4	118	0.620	0.006	0.004	R↓F↓M↓

Source: Processed Data (2023)

Table (4) shows that cluster analysis using the K-means algorithm yields 4 clusters. Cluster 3 has the highest number of members, at 42.45% or 149 members. The cluster that has the lowest members is cluster 2, which has only 0.003% members or only 1 member.

The average value of the RFM variable of the population is 0.64027 (R), 0.03073 (F), and 0.01280 (M). Based on these values, the score of each cluster's RFM variables can be determined and indicated by arrow symbols, whether they are above average or below average.

Table 5. ANOVA Test

Var	Cluster		Error		F	Sig
	MS	df	MS	Df		
R	9.057	3	0.009	347	965.783	0.000
F	0.403	3	0.004	347	94.966	0.000
M	0.332	3	0.001	347	277.628	0.000

Source: Processed Data (2023)

Validation of cluster analysis results was carried out using the ANOVA test. Based on Table (5), we can find out that the significance value of each RFM variable has a value of less than 0.05. This shows that the four clusters formed have R, F, and M values that differ significantly from each other (Aggarwal, 2020).

AHP and CLV Calculation
A pairwise comparison questionnaire was distributed and filled out by decision-making representatives at PT. SI. The representative consists of 1 GM sales & marketing and 3 sales managers. The results of the questionnaire are displayed in the form of an RFM variable matrix in Table (5). The computation was carried out to the RFM variable matrix to obtain the eigenvalue.

Table 5. RFM Variable Matrix

Variable	Recency	Frequency	Monetary
Recency	1	0.3861	0.1111
Frequency	2.5009	1	0,1554
Monetary	9	6,4353	1

Source: Processed Data (2023)

The consistency of the results of the pairwise comparison questionnaire can be calculated using the equation (4). The calculation obtained a CR value of 0.69%. The value is less than 10% and shows that the pairwise comparison assessment conducted by respondents is consistent (Saaty, 2008).

Table 6. Eigenvalue of RFM

Variable	Eigenvalue			Weight
Recency	0.079	0.049	0.088	0.072
Frequency	0.206	0.128	0.123	0.152
Monetary	0.715	0.823	0.790	0.776

λ_{max} : 3,080699
CI : 0,040349
Source: Processed Data (2023)

We can also find out the relative weight value of each RFM variable from Table (6). The Monetary variable has the highest weight with a value of 0.776 (W_M). The Frequency variable has a weight value of 0.152 (W_F). The Recency variable is the variable that has the lowest weight, which is 0.072 (W_R).

The CLV value of each cluster can be calculated using equation (3) after we get the relative weight of each RFM variable. Based on these values, customer clusters can be ranked accordingly.

Table 7. Customer Cluster and CLV Rank

Cluster	N	Score	CLV	Rank
Cluster 1	83	R↓F↓M↓	0.01612	4
Cluster 2	1	R↑F↑M↑	0.99980	1
Cluster 3	149	R↑F↑M↑	0.08889	2
Cluster 4	118	R↓F↓M↓	0.04884	3

Source: Processed Data (2023)

Table (7) shows that Cluster 2 is the first-ranked customer cluster and has a CLV that is significantly different from the other three clusters. The second CLV rank is occupied by Cluster 3 followed by Cluster 4 and Cluster 1 as the third and fourth ranks. CLV ratings will determine the marketing strategy and priority level for each customer cluster.

5. Discussion

Customer Clusters Profile
Cluster analysis resulted in 4 customer clusters with different RFM variable characters and CLV values from each other. Demographic information from customers is added as a consideration in discussing the profile of each customer cluster (Dursun and Caber, 2016). Dachyar et al. (2019) and Paul and Ramanan (2019) named the customer cluster based on that cluster profile.

Cluster 1 profile
Cluster 1 has 83 customers, the third highest in the study. As many as 67.47% of the members of this cluster come from the Oil and gas industry segment. Other industry segments have less than 10% members. The majority of members of this cluster come from the Jakarta area, which is 46.99%, and East Java, which is 13.25%.

Cluster 1 is at the bottom of the CLV ranking. Based on the average value of Recency, this cluster has not made a purchase transaction for a long time (291.64 days) makes it the customer cluster that has the longest last purchase time interval compared to other clusters. The last purchase was made in the first quarter of 2022. Cluster 1 also has an average purchase frequency value of only 1.28 times, the lowest purchase frequency compared to other clusters. The customers in Cluster 1 are dominated by one-time buyer. The same condition also occurs in the average Monetary value, where Cluster 1 only has a total transaction value of USD 4,441.93, the lowest compared to other customer clusters.

Cluster 1 has RFM variable characters that are all far below the population average value (R↓F↓M↓). This indicates that this customer cluster has a low level of loyalty and has no potential to make purchases shortly (Dachyar et al., 2019; Dursun and Caber, 2016). The CLV owned by cluster 1 has the lowest value among other customer clusters, indicating that this cluster has a very low contribution to the company (Pratomo et al., 2019). Therefore, cluster 1 can be referred to as a "Non-Valuable Customer" cluster.

Cluster 2 profile
Cluster 2 only consists of 1 customer or at least among the other clusters in this study. Customer who is members of this cluster come from the Oil and gas industry segment and it is located in Batam, Riau Islands Province.

Cluster 2 is the first-ranked customer cluster with the best CLV. Based on the average value of Recency, this cluster made a recent purchase transaction (2 days) makes it the customer cluster that has the shortest last purchase time interval among other clusters. Cluster 2 also has the highest average purchase frequency among other clusters, which is 145 times. The customer made purchases almost every month in 2022. The same condition is also found in the Monetary value, where cluster 2 has a total purchase transaction value of USD 1,771,389.76, the largest among other customer clusters. The total purchase transaction was approximately 25% of company revenue.

Cluster 2 has RFM variable characters that are all well above the population mean (R↑F↑M↑). This indicates that members of this customer cluster have a high level of loyalty (Dachyar et al., 2019). In line with its RFM character, the CLV of cluster 2 is the highest among other clusters. This indicates that this cluster has a very high contribution to the company (Pratomo et al., 2019). Taking into account the number of members, RFM variable characters, and CLV values, cluster 2 can be named as a "VIP Customer" cluster.

Cluster 3 profile
Cluster 3 has 149 members, the most among the four clusters formed. 49.66% of the cluster members come from the Oil and gas industry segment, 17.45% from Chemical and Refinery, and 10.74% from Power. The locations of cluster 3 members are spread quite evenly throughout the Company's business areas, where Jakarta still dominates with a percentage of 36.24% followed by the East Java and West Java regions with a percentage of 12.75%.

Cluster 3 is ranked second best in the CLV ranking. Based on the average recency value, this cluster last made a purchase transaction 35.57 days ago, lower than the last purchase time interval from the population. Cluster 3 made 9.63 purchases, above the average value of the population. The average value of total purchase transactions (Monetary) Cluster 3 is USD 33,226.21, above the average value owned by the population.

Cluster 3 has RFM variable characters that are all above the population average value (R↑F↑M↑) although not as significant as Cluster 2. However, the Recency value of cluster 3 indicates that the last purchase transaction made was not too long ago and can be an indicator that this cluster tends to buy back shortly (Dursun and Caber, 2016). As the second rank in the CLV ranking, Cluster 3 has an important contribution to the Company, especially since this cluster member is the most compared to other clusters. Therefore, Cluster 3 can be named as a "Valuable Customers" cluster.

Cluster 4 profile
Cluster 4 has 118 members, which makes it the second largest cluster after Cluster 3. 66.10% of the members of this cluster come from the Oil and gas industry segment. Other industry segments have members with percentages below 10%. The locations of customers who are members of this cluster are concentrated in Jakarta with a percentage of 37.29%, Batam with a percentage of 12.71%, and West Java and East Java with a percentage of 11.86%.

CLV cluster 4 ranks third among the 4 clusters formed. Based on the average value of Recency, this cluster has not made a purchase transaction for quite a long time (138.12 days). Cluster 4 has an average purchase Frequency of 1.85 times. As for the average Monetary value, cluster 4 has a total transaction of USD 7,488.63.

The variable RFM character of cluster 4 is not much different from cluster 1. All RFM variable values of cluster 4 are below the population mean (R↓F↓M↓). However, the Recency value of cluster 4 is much better when compared to cluster 1. Despite having low loyalty, cluster 4 still has a higher potential future purchase potential when compared to cluster 1. Paul and Ramanan (2019) mentioned that customer clusters that have similar characteristics to cluster 4 are called customers to be reactivated. Therefore, cluster 4 can be referred to as a "Potentially Valuable Customers" cluster.

Marketing Strategy Recommendations
This research aims to provide recommendations for effective and efficient marketing strategies based on the profile of each customer cluster. Here are 4 recommendations for the 4 customer clusters formed.

Non-valuable customers cluster
The Non-Valuable Customers cluster is the cluster with the lowest CLV value and a very low loyalty rate. The possibility of customers of this cluster to make purchases shortly is almost non-existent. Therefore, the value contribution of this cluster to PT. SI is very low in the present and future.

According to Dachyar et al. (2019), the Non-Valuable Customers cluster has great potential to leave the company. Therefore, the Company is advised not to implement a dedicated marketing program for this cluster. Marketers from the company are strongly discouraged from spending time, energy, and costs to carry out promotional activities in this cluster. The discount policy will tend to have an impact on decreasing company profits compared to increasing the sales value of this cluster.

VIP customers cluster
The VIP Customers cluster is the cluster with the highest CLV value and a very high level of loyalty. The possibility of customers from this cluster making a repurchase shortly is very high (Dursun and Caber, 2016). Therefore, the value contribution of this cluster to the company's profit is very high in the present and the future (Paul and Ramanan, 2019).

The VIP Customers cluster is the most important customer cluster for the company. It is necessary to prepare the best marketing program for this cluster. Moreover, the members of this cluster only consist of 1 customer. According to Pratomo et al. (2019), losing customers from the best clusters can have a negative impact on the company's financial performance.

Several marketing mix strategies can be implemented to increase business value and loyalty from VIP Customers cluster customers, such as ensuring customers are always updated on the latest products or innovations. According to Paul and Ramanan (2019), customers from the best clusters have a role as early adopters of new products and services because they trust in the company and its products. Companies do not need to hesitate to provide the best price to increase the frequency of purchases. Increase transaction comfort and satisfaction by providing easy transaction processes, fast delivery of goods, and responsive after-sales services (Dachyar et al., 2019; Wu et al., 2020). Companies are encouraged to form a dedicated marketing and customer service team for the VIP Customer cluster to ensure that the strategy can run well. Finally, implementing a loyalty program to reward customers from this cluster (Dogan et al., 2018).

Valuable customers cluster

The Valuable Customers cluster is the cluster with the second-best CLV value and has a fairly good level of loyalty. Although the total purchase value is not as large as the VIP Customer cluster, this cluster is predicted to make a repurchase shortly. Therefore, the contribution of this cluster to PT. SI is considered quite important in the present and the future.

A marketing strategy is needed to develop the huge potential of the Valuable Customers cluster. This is because the members of this cluster have the highest number of members among other clusters. Some marketing strategies can be applied such as up-selling and cross-selling strategies to increase the frequency of purchasing the same product or increase total purchases by buying different product lines (Pratomo et al., 2019). Companies need to increase product and brand awareness through exhibitions, seminars, and other promotional activities to increase the frequency of purchases made by customers (Paul and Ramanan, 2019). Marketing strategies can provide competitive price quotes based on customer buying power according to industry segments. Companies need to increase the range of services to customers by establishing branch offices and product distribution in other regions, such as in East Java.

Potentially valuable customers cluster

The Potentially Valuable Customers cluster is the cluster with the second lowest CLV value and low loyalty rate. However, the possibility of this cluster making purchases in the future is still higher than the lowest cluster. It is considered to have potential that can be harvested in the future given the large number of members.

A marketing strategy is needed to capture the potential of this cluster in the future. However, the strategy needs to be prepared carefully so as not to spend company resources. Several marketing strategies can be applied such as conducting customer surveys to be able to find out the level of customer satisfaction, the causes of customer dissatisfaction, and expectations from customers. The company can prepare attractive promotional programs according to the survey results. Dissatisfied customers tend not to trust the company and do not desire to make further purchases (Wu, 2013). Re-sorting products and industry segments that have great contribution potential in the future, for example, focusing on customers from the Oil and gas industry segment. Adopt several marketing strategies from the Valuable Customers cluster to upgrade these cluster customers to better cluster members

6. Conclusions

The customer segmentation process based on the concept of Customer Lifetime Value (CLV) with Recency, Frequency, and Monetary (RFM) modeling resulted in four customer clusters of PT. SI. The four customer clusters formed are given names that represent the characteristics and profiles of each cluster. Marketing strategy recommendations are tailored to these characters and profiles.

The first cluster is the Non-Valuable Customers cluster, which is the cluster with the lowest CLV rating and very low loyalty. The company is advised not to prepare specific marketing strategies for these customer clusters. The second cluster is the VIP Customers cluster, which is the cluster with the highest CLV rating and very high loyalty. Because it has such a significant value contribution, the company is advised to implement the best marketing strategy to maintain customer loyalty in this cluster.

The third cluster is the Valuable Customers cluster, which is the cluster with the second-best CLV rating and good loyalty. In addition, this cluster has the largest number of members among the other four clusters so it has an important contribution to the company. The company is advised to implement up-selling and cross-selling strategies, increase brand awareness, provide competitive price offers, and increase the company's reach to customers. The fourth cluster is the Potentially Valuable Cluster, which has the second lowest CLV value and low loyalty rate. However, the possibility of this cluster making purchases in the future is still higher than the lowest cluster. The company is advised to conduct customer satisfaction surveys and adopt several cluster 3 marketing strategies to be applied to several customers who have sufficient purchasing power.

This research shows that the concept of Customer Lifetime Value (CLV) with Recency, Frequency, and Monetary (RFM) modeling can be used as a basis for grouping customers in B2B businesses. RFM variable values can indicate the characteristics of a customer cluster. CLV rating of each cluster shows the contribution of customers in the present and the future. Both of these can be the basis for developing effective and efficient marketing strategies for each customer cluster.

This research resulted in four customer clusters that have different characters and profiles from each other. These characters come from the interpretation of each RFM variable value owned by each cluster. Through CLV ratings, companies can also identify which customer clusters have a high-value contribution to the Company. Based on this, marketing strategy recommendations are prepared that can be considered by PT. SI is to be applied to each customer cluster. The recommendations aim to increase the value contribution of each cluster and ensure effective and efficient use of resources.

This research has limitations in its implementation. In segmenting customers, only the K-Means algorithm is used. Using other algorithms may result in a different number of clusters. Limited research references similar to B2B business case studies cause marketing strategy recommendations to be less varied. The resulting marketing strategy recommendations may not necessarily be applied to other companies, especially B2C business companies.

Similar research can be further developed to get better results. The use of several cluster analysis methods can be considered to obtain comparisons and determine the best results, especially regarding the number of customer clusters formed. The use of longer data periods can also be considered so that the number of data populations involved in the analysis becomes greater. Further research is also expected to evaluate the results obtained from the implementation of recommended marketing strategies, not just limited to suggestions.

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