Customer Lifetime Value Clustering Using K-Means Algorithm with Length Recency Frequency Monetary Model to Enhance Customer Relationship Management

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ABSTRACT
The current era of business growth is fraught with challenges and competition due to rapid technological advancements, rapid market growth, and globalization. This research discusses customer management strategies to enhance Customer Relationship Management (CRM) at PT Digibook Sarana Promosi Indonesia, a company in the digital printing industry. With the emergence of numerous competitors in this challenging business growth era, the k-means algorithm and Length, Recency, Frequency, Monetary (LRFM) model are employed for customer clustering. The results identify two main customer groups. The first group falls into the category of almost lost or uncertain lost customers with the symbol L↓R↑F↓M↓, exhibiting low Customer Lifetime Value (CLV), suggesting a "let go" strategy to focus on more valuable customers. The second group comprises high-value loyal customers with the symbol L↑R↓F↑M↑, demonstrating high CLV, recommending an "enforced" strategy to maintain customer loyalty through loyalty programs. This research indicates that the optimal number of clusters is 2, validated using the ClValid method, with the best values on connectivity, Dunn index, and silhouette.

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1. INTRODUCTION

The dynamics of intense business competition are driven by rapid market growth, advances in technology, and globalization. Companies must strive to maintain market share amidst increasingly fierce competition. The intensity of business competition urges business players to have reliable skills in understanding customer desires and needs. One effective approach to conducting business is by maintaining a positive relationship with customers, no longer viewing customer transactions as one-time revenue transactions. Customers are the most valuable assets and the key to success in the business world; therefore, many companies compete to attract attention and strive to retain customers (Marisa et al., 2019).

At the beginning of the 20th century, companies generally focused on strategies to attract customers to purchase products. However, eventually, companies decided not only to create products they wanted to sell but also to produce goods or services that matched market demand. Therefore, in the 21st century, a new orientation emerged in the business world emphasizing customer relationship management (CRM) (Novita, 2023). CRM is a strategy implemented by companies to increase sales revenue, attract new customers, and retain existing customer loyalty through customer relationship management by utilizing appropriate concepts, tools, and strategies aimed at overall customer relations and increasing profits (Anshari et al., 2019; Sembiring et al., 2021).(Anshari et al., 2019; Sembiring et al., 2021). Efficient CRM usage can be reinforced by indicators such as Customer Lifetime Value (CLV).

CLV becomes an important metric in measuring the potential value of customers for companies. The CLV model helps design more effective marketing strategies by understanding customer behavior and identifying customer segments that potentially provide the highest profits. The use of k-means clustering algorithms and the LRFM model is an effective approach to grouping customers based on CLV. Each LRFM parameter has weights determined by the Analytical Hierarchy Process (AHP) method. By analyzing customer transaction data and LRFM criteria, companies can identify customer segments with the highest profitability potential (Bakhshizadeh et al., 2022; Rahmadianti et al., 2020). To determine the optimal number of clusters, the elbow method is used to determine the number of clusters to be processed using k-means clustering. This method allows companies to understand customer behavior more deeply and design more accurate CRM strategies (Siagian et al., 2021).

PT Digibook Sarana Promosi Indonesia must face fierce competition in the digital printing industry. To survive, the company needs to design strategies focused on customers to strengthen relationships, increase loyalty, and enhance profitability. In efforts to increase product and service sales, the company needs to design careful strategies that align with market dynamics. This research aims to cluster customers and understand CLV at PT Digibook Sarana Promosi Indonesia using k-means algorithm and LRFM model. Thus, the company can enhance customer experience, strengthen loyalty, and increase revenue with appropriate steps in CRM strategy. With a focus on deeper customer understanding, this research is expected to assist the company in offering more relevant offerings, increasing customer retention and acquisition, and enhancing long-term company success.

2. THE PROPOSED ALGORITHM

2.1. Customer Raleationship Management (CRM)

The user experience of a product can be evaluated using several methods, one of which is using the UEQ and FGD approaches. The UEQ method is an easy-to-apply, valid, and reliable method with subjective quality assessment (Laugwitz et al., 2008). The UEQ consists of 26 items grouped into 6 scales representing different aspects of UX quality (Hinderks et al., 2019). The FGD method is a type of qualitative data collection method that consists of a group of participants together with researchers who gather as a group to discuss a research topic (Mack et al., 2005). Focus groups aim to collect various perspectives from discussion group participants (Anwar & Priharsari, 2021). Focus groups require 5 to 10 participants with recommendations of 6 to 8 participants guided by a moderator who controls the focus of the group to discuss a problem and focus on user interface features with a discussion time duration ranging from 60 to 90 minutes (Adinegoro et al., 2018).

2.2. Customer Lifetime Value (CLV)

To calculate CLV, the required data includes LRFM data from each customer and the assigned weights for each LRFM variable. CLV is obtained by multiplying the LRFM value of each customer by the predetermined weight for each variable. Subsequently, these multiplication results are summed, and the sum is referred to as the CLV value. The use of CLV can assist companies in evaluating customer rankings and is a crucial element in segmentation analysis.

2.3. K-Means Clustering

K-means clustering was first introduced by Lloyd in 1957. However, this method was not formally published in a scientific journal at that time. Then, in 1967, MacQueen proposed the k-means clustering algorithm again, but it was also not published in a scientific journal. It wasn't until 1975 that the k-means clustering algorithm was officially introduced in a paper written by Hartigan. It can be said that Lloyd and MacQueen contributed to the early development of the k-means algorithm, but it was Hartigan who first formally published this algorithm in the context of clustering (Ramadhana et al., 2023). The steps of the k-means algorithm are as follows (Chandra et al., 2021).

1. Determine the number of clusters k.
2. Determine the initial centroids of each cluster.
3. Distribute all data or objects to the nearest cluster. The proximity of a data point to a certain cluster is determined by the distance between the data point and the cluster centroid. The closest distance between a data point and a certain cluster will determine the membership of that data point in a cluster. To calculate the

distance from each data point to each cluster centroid, Euclidean distance theory can be used.

4. The next step is to recompute each cluster centroid.

The basic steps in implementing the k-means method procedure can be seen in Figure 1.

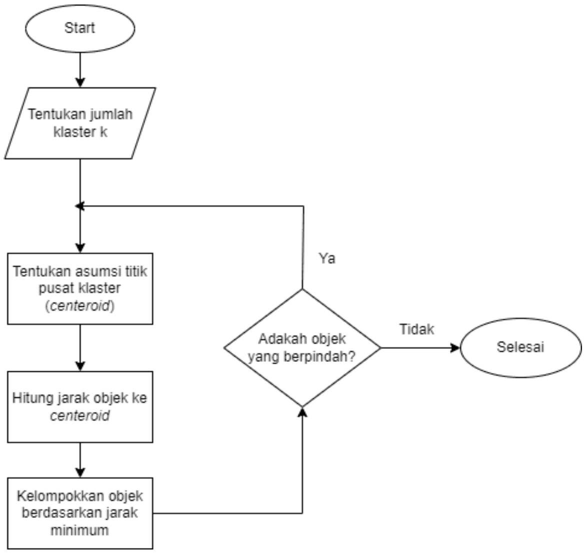

Figure 1. Flowchart K-Means

2.4. LRFM

Length, Recency, Frequency, Monetary (LRFM) is a model used for customer segmentation in customer relationship management (Babaiyan & Sarfarazi, 2019). According to Chang and Tsay (2004) study cited in Reinartz and Kumar (2002), reference, the RFM model has limitations in detecting customer relationships with the company both in the long and short term. Therefore, refinement is done by adding the length index or duration of customer relationships to enable more accurate customer analysis. The duration of customer relationships with the organization reflects the length of time since a customer began to establish a relationship with the Company. LRFM helps companies identify and understand customer characteristics based on four main dimensions: length of relationship with the company (length), time since the customer's last transaction (recency), transaction frequency (frequency), and monetary value of transactions (monetary) (Kandeil et al., 2014).

2.5. Elbow Method

The elbow method is a well-known technique for estimating the required number of clusters as an initial parameter in the k-means algorithm and several other unsupervised machine learning algorithms (Onumanyi et al., 2022). The Sum of Squared Error (SSE) is applied as a performance parameter indicating the proximity of each cluster. When the number of clusters approaches the true number of clusters, SSE demonstrates a significant decrease (Jaafar et al., 2020). The larger the number of cluster values k, the smaller the SSE value will be.

2.6. AHP (Analitycal Hierarchy Process)

Thomas Louis Saaty (1980) from the Wharton School of Business developed a method for determining factor weighting and used it in decision-making involving multiple options. The stages in the Analytic Hierarchy Process (AHP) begin with formulating the problem and constructing a decision hierarchy structure involving consideration factors and alternatives. Subsequently, the construction of pairwise comparison matrices reflects the relative contribution or impact of each element on higher-level goals or criteria. Pairwise comparison matrices are created by comparing two elements one by one. The pairwise comparison scale, established by Thomas. Louis Saaty (1980), utilizes quantitative values ranging from 1 to 9 to assess the level of comparison between criteria. After constructing the pairwise comparison matrices based on the results of questionnaires filled out by respondents, the next step is to find the eigenvalue vector. The eigen value vector is obtained by multiplying each column of the pairwise comparison matrix and then raising it to the power of 1/n (number of variables). Subsequently, determining the values of priority weights and synthesis weights. The stages in the AHP process can be seen in Figure 2.

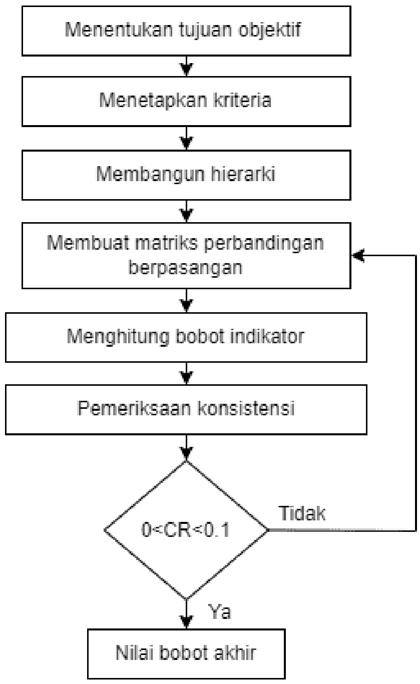

Figure 2. Flowchart AHP

2.7. ClValid

Internal measurements in ClValid include connectivity index, silhouette index, and Dunn index. The connectivity index values range from 0 to infinity. Luthfi et al., (2021) explain that the Dunn index measures the minimum value of the dissimilarity function comparison between two clusters as a separation measure, and the maximum value of cluster diameter as a compactness measure. The Silhouette Coefficient (SC) value is used to measure the confidence level in clustering with a range of interval values between 1 to -1 (Brock et al., 2008). The explanation of SC values is provided in Table 1.

Table 1. SC Value (Kaufman & Rousseeuw, 1990)

No.	The Range of SC	Descriptions
1	0,7 < SC ≤ 1	*Strong structure*
2	0,5 < SC ≤ 0,7	*Medium structure*
3	0,25 < SC ≤ 0,5	*Weak structure*
4	SC ≤ 0,25	*No structure*

When SC equals 1, the object has been successfully placed within the appropriate cluster. With an SC value of 0, the object lies between two clusters. Conversely, if SC is -1, it indicates that the cluster structure suggests the object should be better placed in a different cluster (Yunistya et al., 2022).

3. RESEARCH METHOD

In this study, customer lifetime value clustering was conducted on PT Digibook Sarana Promosi Indonesia's customers to enhance customer relationship management. The K-Means method was employed for data clustering or segmentation of customers using the LRFM parameters. Several stages were undertaken in the data processing process until generating data, which was then analyzed according to the research objectives. The first stage involved data collection obtained from PT. Digibook Sarana Promosi Indonesia, followed by data preprocessing, LRFM modeling, data normalization, LRFM weighting using the AHP method, CLV calculation, k-means clustering, validity testing, and analysis of clustering results. The final stage entailed proposing strategies to improve CRM based on clustering results and CLV calculations. The data analysis stage in CLV clustering to enhance CRM using the k-means algorithm and LRFM model can be seen in Figure 3.

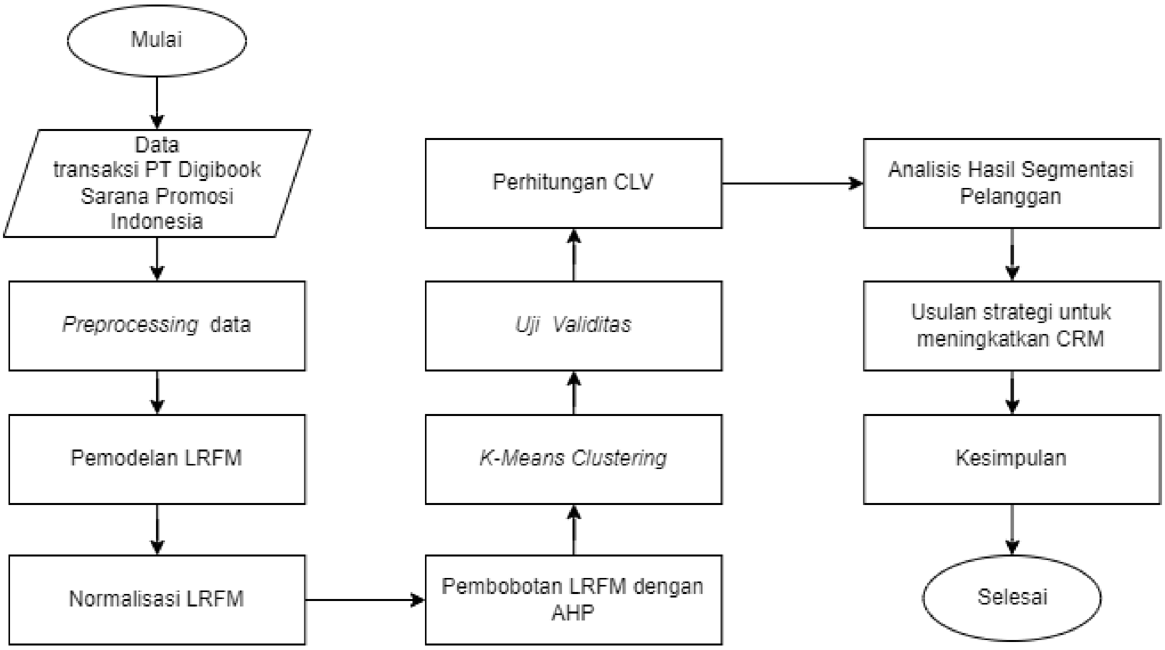

Figure 3. Data Analysis Stage

4. RESULT AND DISCUSSION

In this paragraph, the results and discussion of this research will discuss the findings generated based on the previously outlined methodology. Through a series of research steps undertaken, the authors successfully collected relevant data, analyzed it deeply, and provided profound interpretations of the obtained results.

4.1. Data Preprocessing Results

This preprocessing process involves a series of steps aimed at cleaning, preparing, and transforming data into a more understandable format and ready for processing. These cleaning steps are applied with the goal of improving data processing results and minimizing error rates. The data used in the study includes the sales transaction history of PT Digibook Sarana Promosi Indonesia for the last year, from September 2022 to August 2023. This data was provided on October 30, 2023. The obtained sales transaction history is presented in an Excel document with a total of 24,280 rows of data. There are five attributes subsequently selected according to the LRFM modeling.

4.2. LRFM Modeling

The LRFM modeling is conducted to shape the values of the length, recency, frequency, and monetary variables, which are then utilized as input or input in the clustering process. The transformation of 24,280 rows of data into LRFM modeling yields 1,999 rows of data. The results of the LRFM modeling can be found in Table 2.

Table 2. LRFM Modeling Result

Id	L	R	F	M
00001	304	90	17	1430490
00002	334	90	21	23313100
00003	334	90	15	1393945
....	....	....	....	....
02028	0	59	1	6050
02029	0	59	2	44055
02030	0	59	1	16500

4.3. LRFM Normalization

The normalization of LRFM data is conducted with the purpose of ensuring that the LRFM variables have equivalent values and are within close range. This normalization process is intended to align the scale of the Monetary variable with Length, Recency, and Frequency variables. The normalization method used is Min-Max, aimed at standardizing the values of each LRFM variable to be within the range of 0 to 1. A box plot illustrating the visualization of the normalization results can be seen in Figure 4.

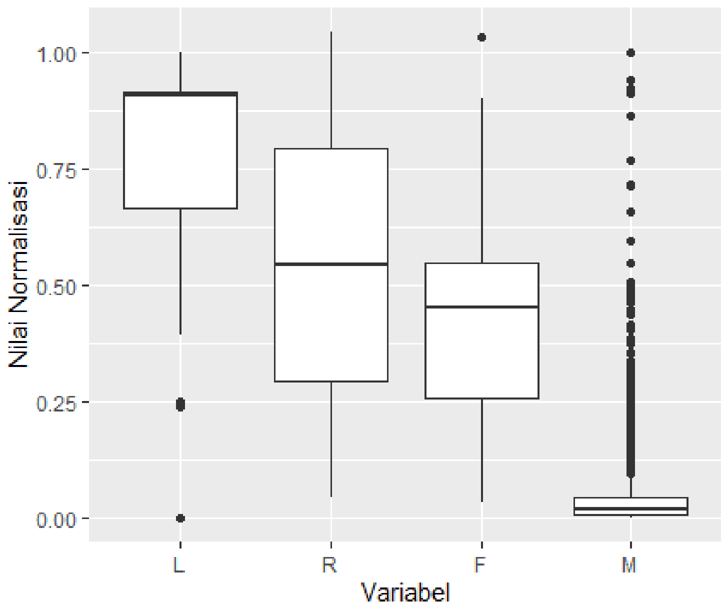

Figure 4. Boxplot After Normalization

Based on Figure 5, it can be concluded that the range of values for the LRFM variable is equivalent and does not show significant differences in comparison to the boxplot before undergoing the normalization process. The results of min-max normalization with a value range of 0 to 1 are presented in Table 3.

Table 3. LRFM Normalization Result

Id	NL	NR	NF	NM
00001	0,846797	0,666667	0,516129	0,031056
00002	0,930362	0,666667	0,645161	0,506679
00003	0,930362	0,666667	0,451613	0,030262
....	....	....	....	....
02028	0	1	0	0,000095
02029	0	1	0,032258	0,000922
02030	0	1	0	0,000323

4.4. The Weighting of LRFM

Weighting of LRFM is conducted using the AHP method. The process of calculating the weights of LRFM is done manually using Microsoft Excel. The data used in the weighting process with the AHP method is the data resulting from the questionnaire filled out by three respondents, namely the director, the manager of merchandiser creative, and the admin from PT Digibook Sarana Promosi Indonesia. From these three data, the average calculation of the three respondents is then performed for subsequent weight calculation using the AHP method, which is processed in the next stage. Table 4 presents the results of LRFM weighting.

Table 4. Normal Comparison Matrix Results

Criteria	*Length*	*Recency*	*Frequency*	*Monetary*	Weight
Length	0,078603	0,140351	0,041863	0,105535	0,091588035
Recency	0,030568	0,052632	0,029481	0,072426	0,046276669
Frequency	0,393013	0,333333	0,185731	0,170202	0,270569831
Monetary	0,497817	0,473684	0,742925	0,651837	0,591565464

4.5. Clustering Result

4.5.1. Determination of the number k

The determination of the value k in this research is conducted using the elbow method implemented in RStudio software. To facilitate the interpretation of optimal cluster analysis results, it can be observed through the visualization of the elbow graph in Figure 5.

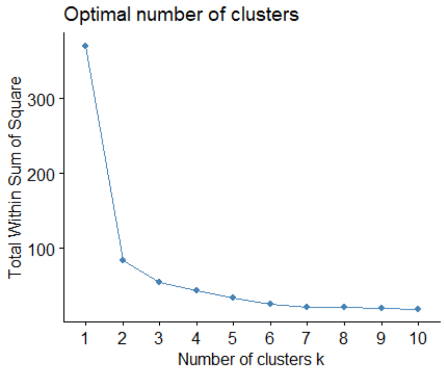

Figure 5. Elbow Chart

Figure 5 illustrates the decrease in SSE values on the elbow graph alongside an increase in the value of k. The figure presents the results of elbow analysis in the form of a two-dimensional plot. The X-axis covers the range of k values from 1 to 10, while the Y-axis indicates the SSE values associated with each k value on the X-axis. It can be observed that the point forming the elbow is at point 2. It can be concluded that based on the graph, the optimal number of clusters is 2 clusters.

4.5.2. K-means Clustering

The data used in this clustering process is customer transaction data that has undergone the LRFM modeling stage and has been normalized. The clustering mapping results for each customer can be seen in Table 5.

Table 5. K-Means Clustering Result

Id	L	R	F	M	Klaster
00001	304	90	17	1430490	2
00002	334	90	21	23313100	2
00003	334	90	15	1393945	2
....	....	....	....	....	....
02028	0	59	1	6050	1
02029	0	59	2	44055	1
02030	0	59	1	16500	1

The clustering results show that cluster 1 consists of 354 customers out of the total number of customers, while cluster 2 comprises 1645 customers out of the total. Figure 4.10 illustrates the percentage of customer clustering results in each cluster. Cluster 1 accounts for 18% of the total customer base, whereas cluster 2 accounts for 82%. The visualization of the clustering results can be seen in Figure 6.

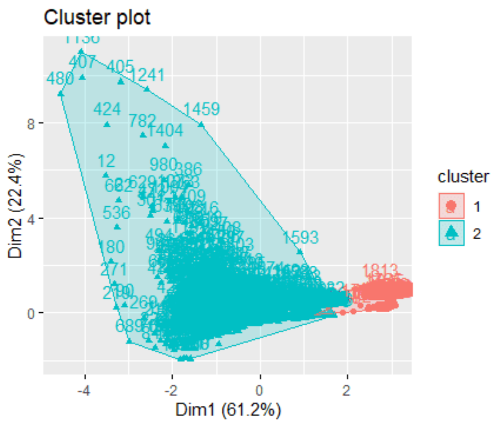

Figure 6. Cluster Plot of Clustering Result

Based on the cluster plot in Figure 6, it shows the result of data clustering with a total of two clusters. The points form lines connected to each other, where cluster 1 is depicted with red color visualization and cluster 2 is depicted with blue color visualization.

4.6. Clustering Validity Test Result

The validation of clustering results is conducted using internal validation through one of the packages available in RStudio, namely ClValid. ClValid is utilized to evaluate or test the performance of the generated clustering model. This function aids in determining the optimal number of clusters produced and evaluating the formed clusters. The results of the validity test using ClValid can be seen in Figure 7.

```
> summary(validity1)

Clustering Methods:
 kmeans

Cluster sizes:
 2 3 4 5 6 7 8 9 10

Validation Measures:
                          2       3       4       5       6       7        8        9       10

kmeans Connectivity  3.0159 40.9492 48.2817 75.8929 99.3004 98.1270 153.0933 155.9587 190.5230
       Dunn          0.1266  0.0080  0.0230  0.0237  0.0242  0.0301   0.0154   0.0154   0.0133
       Silhouette    0.7664  0.5563  0.5538  0.5731  0.5035  0.5004   0.4721   0.4727   0.4573

Optimal Scores:

             Score  Method Clusters
Connectivity 3.0159 kmeans 2
Dunn         0.1266 kmeans 2
Silhouette   0.7664 kmeans 2
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Figure 7. Clustering Validity Result

Figure 7 presents the results of validity testing using ClValid, which indicates that the optimal number of clusters is two, consistent with the initial determination of the number of clusters using the elbow method. The ClValid test on the Connectivity index has the lowest value, which is 3.0159. On the Dunn index, the highest value is 0.1266. Similarly, on the Silhouette index, the highest value among the silhouette values in other clusters is 0.7664, which means SC > 0.7, indicating a strong structure. The higher the SC value, the better the cluster results. An SC value closer to 1 indicates that the data objects have good proximity to their own group and are far from other groups. From these results, the validation test using ClValid with a number of clusters ranging from 2 to 10 clusters shows that k-means clustering can achieve optimal results with a number of clusters of 2.

4.7. CLV Result

The process of calculating CLV involves multiplying the average LRFM variables outcomes from the clustering of each cluster by the LRFM weights predetermined through the AHP method. The CLV calculation results can be found in Table 6.

Table 6. CLV Result

Cluster	Number of Customers	$L*W_L$	$R*W_R$	$F*W_F$	$M*W_M$	CLV	Rangk
1	354	0,0005	0,0449	0,0039	0,0014	0,0072	2
2	1645	0,0808	0,0099	0,1174	0,3060	0,5141	1
Average		0,0407	0,0274	0,0607	0,1537	0,2606	

Based on the data in Table 7 above, it can be concluded that the customer segment showing the highest CLV value is in cluster 2, with a CLV of 0.5141. This segment can be identified by the symbol LRFM L↑R↓F↑M↑, which depicts high-value loyal customers, also known as the best customers with high loyalty levels. In second place, there is cluster 1 with a CLV value of 0.0072 and has the symbol LRFM L↓R↑F↓M↓, indicating lost customers with a level of uncertainty.

4.8. Analysis of Clustering Result

The clustering result using the k-means method revealed two distinct customer groups. From Table 4.15, it is evident that customers belonging to cluster 1 occupy the second position with a total of 354 individuals. The average CLV in cluster 1 is 0.0072, which is lower compared to the CLV value in cluster 2. Customer segment 1 is characterized by the symbol LRFM L↓R↑F↓M↓, indicating uncertain lost customers who exhibit a level of uncertainty. Customers in this cluster tend to infrequently engage in purchase transactions. Generally, customers in this cluster spend relatively small amounts for the company. Although there are some customers who make large transactions, overall, most customers tend to spend smaller amounts in each transaction.

Cluster 2 has the largest number of customers, totalling 1645 individuals. CLV in cluster 2 reaches 0.5141, exceeding the CLV value in cluster 1. With this finding, it can be concluded that customers in cluster 2 can be categorized as high-value loyal customers, representing the best customer group with high customer loyalty, indicated by the symbol LRFM L↑R↓F↑M↑. Customers in cluster 2 tend to spend relatively high amounts for the company.

4.9. Proposed Strategy to Improve CRM

A proposal for strategy to enhance CRM is presented based on the customer segmentation results from Chang and Tsay's (2004) and Marcus's (1998) research. Cluster 1, or uncertain lost customers, falls into segment IV with the proposed marketing strategy being the "let go strategy." By implementing the "let go strategy," the company can optimize its resources to focus on financially more valuable customers, thereby enhancing long-term profitability and business growth. The company can improve customer loyalty in this segment by maintaining communication through periodically sending informative content regarding new products or services without pressuring customers to make purchases. The goal of this strategy is to transform the trend of losing customers into an opportunity to recover relationships and reignite customer interest in transacting again.

Cluster 2 or high value loyal customers are categorized into segment I with the proposed marketing strategy being an "enforced strategy." Customers in this group are the best customers who deserve the most appreciation and special treatment(Marcus, 1998). Considering that these customers have established a long-term relationship with the company, the customer group in this cluster is referred to as loyal customers. Therefore, a strategy is needed to increase customer loyalty. This opinion is supported by Dharmalingam et al. (2011) who argue that it is better to retain existing customers before acquiring new ones. According to Cengiz dan Yayla (2007), the cost of acquiring new customers is five times higher than the cost of retaining existing customers. This strategy aims to build deeper closeness with loyal customers, increase engagement, and maintain sustainable relationships.

5. CONCLUSION

Business development faces complex challenges and fierce competition PT Digibook Sarana Promosi Indonesia, a company operating in the digital printing sector, is facing increasingly tight competition due to the emergence of various new competitors. The k-means algorithm and the Length, Recency, Frequency, Monetary (LRFM) model are used to cluster customers and analyse CLV with the aim of improving CRM. The implementation of the k-means algorithm resulted in two customer clusters. The first cluster consists of 354 customers, accounting for 18% of the total customers, while the second cluster consists of 1645 customers, accounting for 82% of the total customers. Cluster validity testing was identified using the ClValid cluster validation method. Based on the analysis results, cluster 1 shows uncertain lost customer behaviour patterns with an average CLV of 0.0072. Most customers tend to make small transactions, with relatively low expenditures.

Cluster 2 exhibits high-value loyal customer behaviour patterns with an average CLV of 0.514. Customers in this cluster tend to make large transactions and have high levels of loyalty. For cluster 1, a "let go strategy" approach is recommended where the company focuses on more valuable customers by reducing excessive retention efforts towards customers who contribute little to the company's revenue. For cluster 2, it is recommended to implement an "enforced strategy" by strengthening relationships with loyal customers through loyalty programs, priority services, and targeted communication to maintain customer loyalty in the long term.

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