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New Approach: Customer Segmentation using RFM Model and Demand Classification

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ABSTRACT

This research introduces an integrated data mining framework that combines RFM (Recency, Frequency, Monetary) analysis with demand pattern classification—encompassing Smooth, Erratic, Intermittent, and Lumpy categories—to refine customer segmentation strategies. While RFM effectively captures transactional behavior, its scope remains insufficient as it overlooks demand variability and intermittency, which critically influence purchasing dynamics and inventory planning. By incorporating demand classification, this model addresses behavioral dimensions beyond conventional transactional metrics, thereby enhancing segmentation precision and strategic relevance. Customer clustering employs the K-Means algorithm, with cluster optimization validated through Elbow Method and Silhouette Index analyses, yielding five distinct segments: Ideal, Interest, Improve, Inconsistent, and Inactive. Subsequently, Customer Lifetime Value (CLV) is computed by weighting RFM and demand parameters via Analytic Hierarchy Process (AHP), with Consistency Index and Consistency Ratio assessments ensuring methodological rigor. Results are synthesized within an interactive dashboard, facilitating data-driven decision-making in retention strategies, inventory optimization, profitability enhancement, and sustainable business development.

INTRODUCTION

In modern business competition, the cost of acquiring new customers is relatively higher compared to retaining existing ones, since data on current customers is already available [1]. Therefore, customer segmentation becomes a key factor in understanding behavior and characteristics, then designing effective marketing strategies [2]. One of the most widely used methods is RFM (Recency, Frequency, Monetary) analysis, which enables companies to identify high-value customer segments and calculate Customer Lifetime Value (CLV) [3]. CLV reflects customer retention, loyalty, and profitability [4], where strong retention through repeat purchases contributes significantly to profit growth [5]. However, pure RFM analysis has inherent limitations because it relies solely on transactional recency, frequency, and monetary value, without capturing the variability, stability, or predictability of customers' demand behavior. To enhance segmentation accuracy, clustering techniques such as the K-Means algorithm are increasingly used to group customers based on multiple behavioral attributes [32].

The main challenge in customer retention lies in demand uncertainty [6], which can increase inventory costs, raise the risk of stockouts, and reduce customer satisfaction [7]. Such conditions are often caused by sudden large-scale demand, slow-moving products, and sporadic demand patterns [8]. To understand these patterns, two key parameters are used: the

Demand Variation Coefficient (CV^2), which reflects quantity variability, and the Average Demand Interval (ADI), which indicates demand intermittency. These two parameters classify demand into four (4) categories: smooth, erratic, intermittent, and lumpy [9]. Integrating Demand Classification with RFM addresses the limitations of pure RFM because CV^2 and ADI provide additional behavioral insights that identify whether customers exhibit stable, volatile, or highly intermittent demand profiles.

Understanding this classification is crucial for organizations or companies to balance inventory requirements, reduce stockout risks, adjust volumes, accelerate fulfillment times, and minimize logistics costs [8]. Consequently, competitiveness increases, inventory efficiency is maintained, customer service improves, and satisfaction remains intact [10]. When integrated with RFM analysis, demand classification provides a clearer and more comprehensive understanding of customer purchasing behavior and spending patterns, as well as the demand trends of each customer segment in relation to inventory management [18]. Along with the shift in business orientation, many companies are now adopting a customer-centric approach, placing customers at the center of decision-making [11]. Customer segmentation plays an essential role in supporting customer-oriented strategies [14], as it enables companies to gain deeper insights into customer needs and satisfaction levels, thereby strengthening loyalty [19].

Nevertheless, the product-centric perspective remains relevant, particularly in ensuring product availability in response to market demand. A holistic approach integrates RFM analysis [12] for customer segmentation with Demand Classification (CV^2 and ADI) for inventory demand patterns. Additionally, the Analytic Hierarchy Process (AHP) [31] is applied to assign weights in determining CLV [15]. The specific contribution of this research lies in developing an integrated segmentation framework that combines RFM, demand classification, and AHP-based weighting to produce a more comprehensive and operationally relevant CLV assessment [16]. This integrated approach allows for more accurate segmentation, helps organizations or companies identify high-value customer groups, and supports business strategies that effectively and efficiently align marketing (customer) and inventory management (product). Striking a balance between customer understanding and product management becomes a key factor in sustaining competitiveness in today's dynamic marketplace.

METHODS

This study comprised four stages: data collection encompassing customer transactions and products; data preprocessing for cleaning and normalization; segmentation analysis integrating RFM with Demand Classification using K-Means clustering, optimized via Elbow Method and Silhouette Index; and customer valuation through AHP with Consistency Index/Ratio validation, followed by Customer Lifetime Value calculation and interactive dashboard visualization using Google Colab, SPSS, Excel, and Power BI. [11], [14].

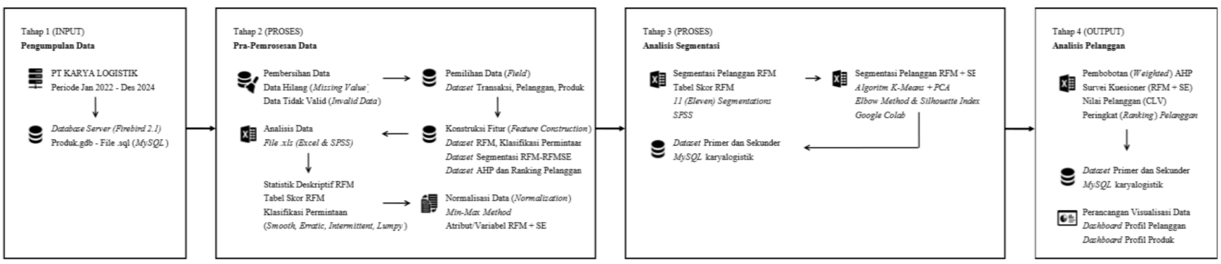

Figure 1. Research Methodology Stages (Input - Process - Output)

Data Collection

Data were collected from PT Karya Logistik, (website: https://karyalogistik.id) a Cahaya Matahari Group subsidiary established in 1984, specializing in power machinery distribution for agricultural and fisheries sectors. Primary data comprised systematic observation of approximately 4,500 transactions, 400 customers, and 600 products (January 2022–December 2024) from the Sumatra Branch database, alongside structured questionnaires administered to branch management for AHP-based CLV weighting. Secondary data incorporated documentary analysis and scholarly references supporting primary findings.

Data Pre-Processing

In the second stage of this study, data preprocessing was carried out to transform the primary transaction and customer data into a secondary RFM dataset in accordance with the RFM model criteria [29]. The transaction data covered the period from January 2022 to December 2024, with December 31, 2024, established as the reference date for calculating the Recency (R) attribute. This attribute was computed based on the number of days between a customer's most recent transaction and the reference date. The Frequency (F) attribute was obtained from the total count of unique transactions (Distinct Transaction IDs), while the Monetary (M) attribute was derived from the total transaction value of each customer within the same period [30].

Table 1. RFM Score Quintile [12]

Score	Recency	Frequency	Monetary
5	Very Recent	Very Frequent	Very High
4	Recent	Frequent	High
3	Standard	Normal	Normal
2	Not Recent	Rare	Low
1	Long Ago	Very Rare	Very Low

The scoring process was conducted by assigning values from 1 to 5 for each R, F, and M variable using the quintile method [4]. This method divides the data into five (5) equally proportioned groups (20%) based on the minimum, maximum, 25%, 50%, and 75% percentiles [11]. For the recency attribute, customers with the most recent transaction dates were assigned the highest score (5), while the scores decreased as the transaction recency became more distant [13]. A similar principle was applied to the frequency and monetary attributes, where higher transaction counts or higher purchase values corresponded to higher scores [14]. The final result was a combined RFM score that categorized customers, for example 113, 514, 342, 215, with 555 representing the best category and 111 representing the lowest [27]. To ensure more accurate analysis, the RFM data were normalized using the Min-Max method [2], which mapped values into a range of 0–1 to address differences in scale across the RFM variables [15]. In addition, descriptive statistical analysis was performed, covering minimum, maximum, mean, standard deviation, as well as percentile distributions (25%, 50%, 75%) to provide an initial overview of the dataset characteristics [22].

Table 2. Customer RFM Scoring

ID Customer	Customer Name	R	F	M	Score	RFM Segments
ABR-SITEK	SINAR TEK*****	2	4	5	245	LOYAL CUSTOMERS
APD-RBM	RBM-KOT*****	3	3	4	334	LOYAL CUSTOMERS
MDN-RAKS	RAKSASA D******	1	1	2	112	HIBERNATING
…	…	.	.	.	.	.
RBS-SUDIS	SUMBER DI*****	2	5	5	255	LOYAL CUSTOMERS

In addition to the pre-processing of the RFM model, further preprocessing was conducted for product demand classification based on two key parameters: the CV^2 and the Average Demand Interval (ADI) [8]. The demand classification applied in the data pre-processing stage of this study refers to the method developed by Syntetos, Boylan, and

Croston, which integrates multiple analytical criteria to better understand the characteristics of demand patterns. This method divides demand patterns into four categories, smooth, erratic, intermittent, and lumpy [9], using two main parameters: the squared coefficient of CV^2 on the Y-axis and the ADI on the X-axis [17]. CV^2 is defined as the squared ratio of the standard deviation to the mean demand, representing the level of demand variability [18]. Meanwhile, ADI is the average interval between demand transactions, indicating the degree of intermittency or fluctuation in the demand periods [20].

$$CV = \frac{\text{Demand Standard Deviation}}{\text{Demand Mean}} \qquad CV^2 = \left(\frac{\sqrt{\sum_{i=1}^{n} (e_i - e_a)^2 / n}}{e_a} \right)^2$$

Where:

CV = Coefficient of Variation Value, e_i = Product Demand Value in a certain period i,

e_a = Average Product Demand Value, n = Number of Time Periods

$$ADI = \frac{Total\ Periods}{Total\ Demand\ Buckets} \qquad ADI = \frac{\sum_{i=1}^{n} p_i}{n}$$

Where:

ADI = Average Demand Interval Value, p_i = Total Number of Periods,

n = Total Demand Buckets (Number of Periods with Non-Zero Demand) with Transactions,

i = Demand Period Index Value

The threshold values for the CV^2 and ADI parameters in demand classification were set at $CV^2 = 0.49$ and ADI = 1.32 [6], as illustrated in Figure 2.7 [10]. Based on these two parameters, demand patterns are categorized into four quadrants [18], namely:

- Smooth (Stable Demand): demand occurs regularly and routinely in almost every period [10], with low CV^2 and low ADI (ADI < 1.32 and $CV^2 < 0.49$) [18].
- Erratic/Irregular Demand: demand occurs routinely [10], but with high variation in quantity, characterized by high CV^2 and low ADI (ADI < 1.32 and $CV^2 \geq 0.49$) [18].
- Intermittent Demand: demand occurs less frequently with low variation in quantity [10], but the intervals between periods are relatively long, characterized by low CV^2 and high ADI (ADI ≥ 1.32 and $CV^2 < 0.49$) [18].
- Lumpy (Unstable Demand): demand shows both high quantity variability and long-interval fluctuations [10], with high CV^2 and high ADI (ADI ≥ 1.32 and $CV^2 \geq 0.49$) [18].

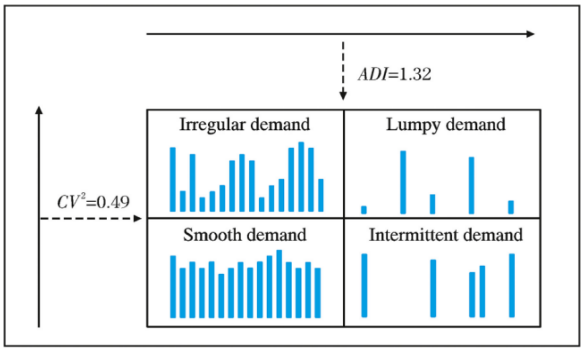

Figure 2. Demand Classification [9]

Based on the observed demand pattern, the classification of the product's demand can be characterized by regular demand occurrences over time, accompanied by a high degree of variability in the quantities requested. The demand profile indicates short intervals between demand periods (reflecting routine demand), together with a high CV^2 and a low ADI [10].

Segmentation Analysis

In the third stage of this study, customer segmentation analysis was conducted through data pre-processing using the RFM (Recency, Frequency, Monetary) method. The scores from these three variables were combined to form customer segments, which then served as the basis for segmentation analysis. Based on the combination of RFM scores, customers were grouped into several segments, including Loyal, New Customers, Potential, Hibernating/Lost, and At Risk. This segmentation allows companies to better understand the structure of their customer base while designing marketing strategies tailored to the characteristics of each segment. For example, loyal customers may be offered exclusive membership programs to maintain retention, passive customers can be targeted with promotions or discounts to encourage repeat transactions, while potential customers can be directed through bundling offers or personalized communication to increase the likelihood of becoming active and loyal customers.

After obtaining the RFM segmentation results, the next step was to perform RFM and Demand Classification segmentation, which combines the RFM variables with the Demand Classification variable. All data were first normalized and then analyzed using the K-Means clustering algorithm. Since there were more than two variables, visualization was performed using Principal Component Analysis (PCA) to reduce the data into two main dimensions without losing important information [2]. The PCA results produced two components, namely PC1 and PC2 [26]. The first dimension (PC1) represents customer purchasing behavior and habits, with dominant contributions from Frequency (0.605733) and Monetary (0.568048), thereby reflecting transaction intensity. The second dimension (PC2) illustrates customer demand, dominated by the Smooth–Erratic variable (0.847580), while the Recency variable contributed relatively little to both dimensions (PC1 = –0.455947; PC2 = –0.250290).

Table 3. Customer Segments Based on the RFM Model [27]

Customer Segments	R	F & M	Number of Customers	Percentage (%)
Champions	4-5	4-5	16	4.00%
Loyal Customers	2-5	3-5	65	16.25%
Potential Loyalist	3-5	1-3	39	9.75%
Recent/New Customers	4-5	0-1	-	0.00%
Promising	3-4	0-1	-	0.00%
Need Attention	2-3	2-3	9	2.25%
About to Sleep	2-3	0-2	3	0.75%
At Risk	0-2	2-5	27	6.75%
Can’t Lose Them	0-1	4-5	-	0.00%
Hibernating	1-2	1-2	5	1.25%
Lost	0-2	0-2	236	59.00%

Based on the PCA results combined with the K-Means clustering algorithm, four (4) customer segment clusters were formed, namely Ideal, Interest, Improve, and Inactive. The X dimension (PC1) reflects transaction activity, while the Y dimension (PC2) represents customer demand. The description of each customer segment’s characteristics is presented in Table 4 below.

Tabel 4. Characteristics of RFM Model Segmentation and Demand Classification

Segment	Description
Ideal	Active customers, with high purchase value, frequent shopping, and recent purchases. Their purchasing needs are for products with a stable demand pattern (Smooth). They are highly loyal and valuable to the company.
Interest	Customers with high potential, active but not yet optimized, showing high purchasing activity and frequency with still significant purchase value. Their product needs fall

	within a stable-to-erratic demand pattern, indicating a transition phase.
Improve	Regular or less active customers, but still with potential for improvement, as they still show fairly frequent purchasing, with purchase values sometimes still significant. However, their product needs correspond to an irregular or non-routine demand pattern (Erratic–Intermittent).
Inactive	Passive customers, with small or low purchase value, inconsistent, and infrequent purchases. Their purchasing needs are for products with an unstable demand pattern (Intermittent–Lumpy).

Customer Analysis

The final stage of this research involved distributing written questionnaires (based on the RFM Model and Demand Classification) to the Branch Head, Head of Sales, and Head of Administration as stakeholders directly involved in the operations of PT Karya Logistik, Sumatra Branch (Medan). The questionnaire data were then analyzed using the AHP method [15]. The results indicated that the Consistency Index (CI) and Consistency Ratio (CR) values were within the acceptable threshold (< 0.1) [16], confirming that the obtained priority weights are consistent and valid. These weights were subsequently used as the basis for calculating CLV and ranking customers [22].

Table 5. RFM + Demand Classification Comparisson Matrix by Respondent Branch Head

Criteria	Recency	Frequency	Monetary	Demand Classification
Recency	1.0000	1/5 (0.2000)	1/7 (0.1429)	1/3 (0.3333)
Frequency	5.0000	1.0000	1/3 (0.3333)	3.0000
Monetary	7.0000	3.0000	1.0000	3.0000
Demand Classification	3.0000	1/3 (0.3333)	1/3 (0.3333)	1.0000
Total	**16.0000**	**4.5333**	**1.8095**	**7.3333**

Table 6. Eigenvalues Based on the Responses of the Branch Head

Criteria	R	F	M	DC	Amount	Weighted	Eigen Value
Recency	0.0625	0.0441	0.0789	0.0455	0.2310	0.0578	0.9241
Frequency	0.3125	0.2206	0.1842	0.4091	1.1264	0.2816	1.2766
Monetary	0.4375	0.6618	0.5526	0.4091	2.0610	0.5152	0.9324
Demand Classification	0.1875	0.0735	0.1842	0.1364	0.5816	0.1454	1.0663
Total	**1.0000**	**1.0000**	**1.0000**	**1.0000**	**4.0000**	**1.0000**	**4.1993**

Table 7. Calculation of Consistency Index (CI) From Respondents

Respondent	Eigen Value	Number of Criteria	Consistency Index (CI) Value
Branch Head	4.1993	4.0000	0.0664
Sales Head	4.2593	4.0000	0.0864
Administration Head	5.7225	4.0000	0.5742

The CR value of 0.6380 substantially exceeds the acceptable tolerance threshold of 0.10. This condition indicates that the pairwise comparisons provided by the third respondent are insufficiently consistent, resulting in invalid priority weight outcomes. Based on the recap of the CI/CR from all three respondents, as presented in Table 8, it is observed that only two out of the three respondents meet the acceptable consistency criterion, indicated by a CR of less than 0.10.

Table 8. AHP Consistency Index Value and Consistency Ratio

Respondent	CI	RI	CR	Flag/Status
Branch Head	0.0664	0.9000	0.0738	CONSISTENT
Sales Head	0.0864	0.9000	0.0960	CONSISTENT
Administration Head	0.5742	0.9000	0.6380	INCONSISTENT

Table 9. Final Weighted AHP Score

Respondent	Recency	Frequency	Monetary	Demand Classification
Branch Head	0.0578	0.2816	0.5152	0.1454
Sales Head	0.5911	0.1706	0.1234	0.1150
Final Weighted Value	**0.3244**	**0.2261**	**0.3193**	**0.1302**

The calculation of CLV was carried out by multiplying the normalized variable values (nR, nF, nM, nDC) with the corresponding priority weights obtained from the AHP method (wR, wF, wM, wDC) [15]. The results of these multiplications were then summed to obtain the CLV value for each customer [16].

$$CLV = \frac{(wR \text{ x } nR + wF \text{ x } nF + wM \text{ x } nM + wDC \text{ x } nDC)}{wR + wF + wM + wDC}$$

Where:
CLV = Customer Lifetime Value, *nR, nF, nM, nDC* = Normalized Value of Recency, Frequency, Monetary, Demand Classification, *wR, wF, wM, wDC* = Weighted Value of Recency, Frequency, Monetary, Demand Classification Variables

Table 10. Customer Ranking

ID Customer	Customer Name	Score	RFM Segments	CLV	*Rank*
ABR-SITEK	SINAR TEK*****	245	LOYAL CUSTOMERS	0.1757	64
APD-RBM	RBM-KOT*****	334	LOYAL CUSTOMERS	0.1888	53
MDN-RAKS	RAKSASA D******	112	HIBERNATING	0.1666	80
…	…	.	.	.	.
RBS-SUDIS	SUMBER DI*****	255	LOYAL CUSTOMERS	0.2581	19

Subsequently, the CLV of each customer was sorted from the highest to the lowest, thereby producing a systematic customer ranking.

RESULTS AND DISCUSSION

Based on the segmentation analysis of the RFM model and demand classification in Figure 4, four clusters were identified as the optimal result. The evaluation using the Elbow Method indicated an elbow point at the fourth cluster, with a WCSS reduction of 4.28. As shown in Figure 3, the WCSS sharply decreases at clusters 2 and 3, remains significant up to cluster 4, but slows down after cluster 5. Therefore, four clusters were selected as the optimal number, as they provide a balanced trade-off between model complexity and segmentation quality.

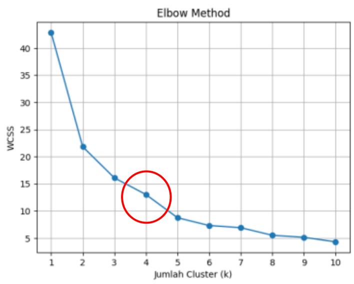

Figure 3. Elbow Point Graph of RFM Model Segmentation and Demand Classification

Table 11. WCSS Values of RFM Model Segmentation and Demand Classification

Cluster (k)	WCSS Values	WCSS Reduction Difference
1	42.858184	-
2	21.820361	21.04
3	16.091897	5.73
4	**13.025506**	3.07
5	8.748930	**4.28**
6	7.313494	1.44
7	6.917719	0.40
8	5.516068	1.40
9	5.146139	0.37
10	4.311899	0.84

The Elbow Method (WCSS) evaluation indicated that the most optimal number of clusters was at k = 4. The elbow point was clearly observed, with a significant reduction in WCSS up to the fourth cluster, while the decreasing trend slowed after the fifth cluster. This condition confirms that four (4) clusters are sufficient to represent the balance between model complexity and segmentation quality. To reinforce this finding, an additional analysis was conducted using the Silhouette Score (SI) within the range of k = 2 to k = 10. The highest score was recorded at k = 2 with 0.4597, indicating the technically most optimal cluster separation. However, dividing the dataset into only two (2) clusters was considered overly simplistic and insufficient to capture the diversity of customer characteristics. Another alternative appeared at k = 5 with a score of 0.4103, which, although lower than k = 2, still demonstrated good separation quality while offering more detailed and stable segmentation.

When associated with the WCSS evaluation, both four and five clusters can be considered viable solutions. Four clusters provide a balance between model simplicity and segmentation accuracy, while five clusters offer richer analytical depth and greater relevance for the company’s strategic and operational needs. Therefore, the optimal number of clusters can be established in the range of 4 to 5, depending on the objectives of the analysis and the business priorities to be achieved. Previously, the Elbow Method indicated that the optimal number of clusters was four, namely Ideal, Interest, Improve, and Inactive. However, the Silhouette Score results suggested that the addition of a fifth cluster generated an additional segment, namely Inconsistent, which lies between the Improve and Inactive clusters. This cluster represents customers with inconsistent purchasing patterns who may potentially be in a transitional phase, either toward improvement or decline. Identifying the inconsistent cluster is crucial, as it enables the company to implement early strategic interventions to guide these customers toward more positive segments, such as Improve or Ideal.

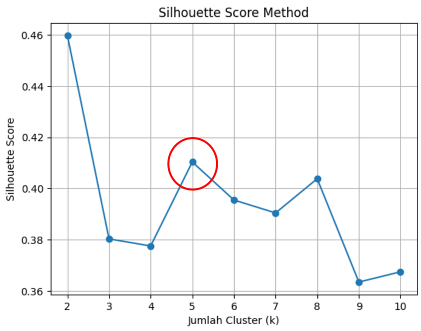

Figure 4. Silhouette Score Graph of RFM Model Segmentation and Demand Classification

Table 12. Silhouette Score (SI) Score

Cluster (k)	Score SI
2	0.4597469711268437
3	0.3802868436775688

4	0.377534379116803
5	**0.41031883275581865**
6	0.3954814964973178
7	0.3904291345905772
8	0.40378328685312614
9	0.36344192526989605
10	0.3674475371820014

These findings show that incorporating demand-pattern attributes strengthens customer differentiation by capturing behavioral variations beyond transaction frequency and value. The Ideal and Interest clusters demonstrate strong and consistent demand, making them prime targets for loyalty and membership development. The Improve cluster holds moderate potential that can be enhanced through targeted engagement, while the Inactive cluster exhibits declining activity and higher churn risk, requiring focused retention measures. The inconsistent cluster indicates irregular demand that calls for better alignment between products and customer needs. Overall, this enriched segmentation framework supports more precise strategies for sustaining valuable customers and reactivating those with recoverable potential.

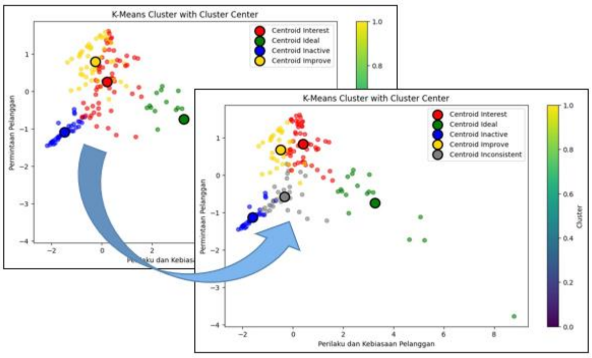

Figure 5. RFM Model Segmentation Analysis and Demand Classification (k=5)

CONCLUSIONS AND RECOMMENDATIONS

This research implemented an integrated RFM and Demand Classification framework at PT Karya Logistik, Sumatra Branch. The analysis identified four primary customer segments—Ideal, Interest, Improve, and Inactive—validated through the Elbow Method (WCSS = 13.0255 at k = 4). Supplementary Silhouette Index evaluation (SI = 0.4103) revealed a fifth segment, Inconsistent, representing customers exhibiting irregular purchasing patterns between the improve and inactive categories. Demand analysis predominantly identified lumpy patterns, characterized by significant fluctuations causing supply-demand misalignment, consequently placing 59% of customers in the lost segment with elevated churn risk.

Notably, conventional RFM classifications (e.g., Loyal Customers) inadequately reflected actual customer value without demand considerations; customers deemed Loyal under traditional RFM appeared Inactive when demand patterns were integrated. Customer Lifetime Value rankings, weighted heavily toward Recency (0.3244) and Monetary (0.3193) variables, occasionally diverged from segmentation outcomes due to methodological differences between weighted prioritization and clustering algorithms. Future research should contextualize demand thresholds (CV^2 = 0.49; ADI = 1.32) across sectors and incorporate price sensitivity variables to capture comprehensive behavioral dimensions influencing purchasing decisions and customer valuation.

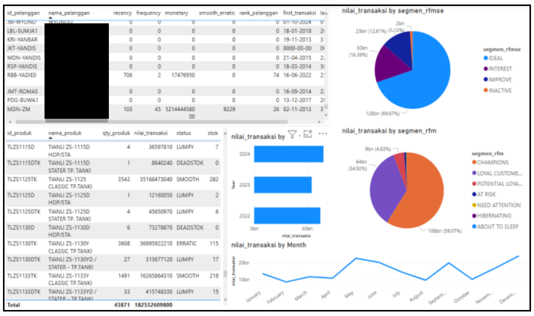

Figure 6. Customer Profile Dashboard

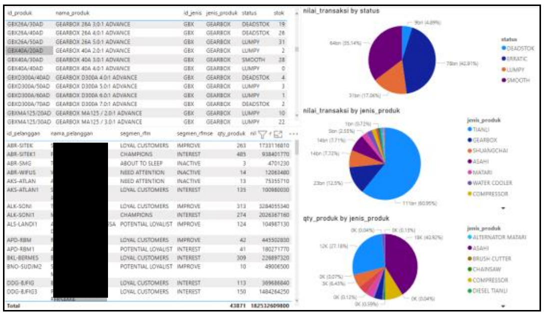

Figure 7. Product Profile Dashboard

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