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K-Means Clustering of Product Sales Patterns for Inventory Management at Fahra Jaya Store

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ABSTRACT

Sales transaction data play a crucial role in supporting business decision-making. However, in many grocery stores, including the Fahra Jaya Store, transaction data are often simply stored without further analysis, resulting in inventory management that relies heavily on the owner's judgment. This study applied K-Means clustering to group products based on sales patterns and develop inventory recommendations. Sales transaction data from January through October 2025 at the Fahra Jaya Store were collected and preprocessed, resulting in 1,003 valid product records. The clustering process used three variables: number of units sold, average sales, and sales growth, yielding three distinct clusters. Cluster 0 (31 products) exhibited high sales and moderate growth; Cluster 1 (93 products) showed the highest growth from a low sales base; and Cluster 2 (879 products) represented low sales and growth. The Davies-Bouldin Index (DBI) yielded a value of 0.638. The choice of k = 3 was examined by comparing it against k = 2 through 6 using the Elbow method, DBI, and cluster size balance. Although the lowest DBI occurred at k = 4 (0.494), it resulted from a cluster containing only a single product; therefore, k = 3 was retained. The clustering results were interpreted to formulate specific recommendations: maintaining stock for high-sales products (Cluster 0), increasing stock gradually for products with rising demand (Cluster 1), and evaluating low-sales products individually before reducing stock (Cluster 2).

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1. INTRODUCTION

The retail sector, particularly grocery stores, plays a strategic role in supporting economic growth and fulfilling the daily needs of the community [1], [2]. Despite the rapid advancement of information technology, many small and medium-sized retail enterprises (SMEs) struggle to adapt, often leaving their transaction data underutilized [3]. A common problem in the retail sector is that sales data is merely stored as an archive rather than analyzed to identify market trends and optimize inventory [4]. This exact situation is clearly evident at Fahra Jaya Store, a grocery store that sells a wide variety of daily necessities. Based on interviews and observations with the store owner, inventory replenishment decisions were found to still rely primarily on subjective judgment rather than available sales data, despite the store having a computerized system that records transaction data. This makes it difficult for the store owner to identify products with increasing, moderate, or low sales over time [5].

As a consequence, improper inventory management poses significant risks to operational efficiency. Stockouts can result in lost sales opportunities and reduced customer satisfaction, whereas overstocking increases storage costs and the risk of product expiration [6], [7]. To address these issues at Fahra Jaya Store,

data mining techniques were used to extract hidden patterns from sales transaction data and transform them into useful information for decision-making. One of the techniques used was K-means clustering, which groups data with similar characteristics without predefined class labels. This algorithm was chosen for its simplicity, computational efficiency, and ability to identify product groups with similar sales characteristics [4], [8].

Previous studies have demonstrated the effectiveness of the K-Means algorithm for clustering sales data. Among these studies, Yahya and Kurniawan applied the K-Means method to cluster sales data from the Aceh Mulia Grocery Store using 30 datasets that included product names and sales volumes, in order to identify the products most in demand by customers and to categorize products into best-sellers and slow-sellers [9]. Similarly, Damayanti and Putri applied the K-Means algorithm to analyze rice sales patterns and identify consumer segments based on purchasing characteristics including sales volume, purchase frequency, and price by grouping products into three tiers (unpopular, popular, and very popular) [10]. Both studies characterize products mainly by how much they sell, and neither includes a measure of how fast its sales are changing. That matters because two products can have similar sales totals but move in opposite directions. One may be picking up while the other is slowly fading, and a grouping based on totals alone puts them together [9], [10].

Other researchers have looked at this problem from the time-series side. Bozanta et al. clustered grocery products by how their sales and prices change over time, using daily data from an online grocery company and a public retail dataset [11]. They also point out that distance measures based only on numerical closeness can miss how products move over time [11]. Their approach, though, relies on long daily records and a custom distance measure, which is not easy to apply to a small store whose records are monthly.

Sales volume only shows how much a product sold during a period [12]. It says nothing about where sales are heading, so two products that sell about the same amount can look identical even if one is picking up and the other is slowing down. Sales growth fills this gap, because it shows whether demand for a product is rising or falling over time [13], [14]. For this reason, this study adds sales growth to the clustering, together with total units sold and average monthly sales, so that low-selling products that are gaining ground can be told apart from those that are not.

Accordingly, this study applies the K-Means clustering algorithm to examine how adding sales growth, together with total units sold and average monthly sales, changes the way products are grouped at Fahra Jaya Store. The resulting clusters are expected to provide a basis for data-driven inventory recommendations that fit the sales characteristics of each product group. Through this approach, this study makes three major contributions. First, it integrates the sales growth variable (measured based on the average monthly change in units sold from February through October 2025) into the K-Means analysis for small grocery stores. Second, it translates the characteristics of each cluster into practical inventory management actions for store owners, namely: maintaining stock for high-selling products, increasing stock gradually for products with rising demand, and evaluating low-selling products one by one before reducing stock. Third, it comprehensively documents the data preprocessing steps, the rationale for determining the number of clusters, and the software configuration so that this method can be replicated by MSMEs or other similar stores.

2. METHOD

This study employs a descriptive quantitative approach by applying data mining techniques using the K-Means Clustering algorithm to identify product sales patterns at Fahra Jaya Store. The research stages included data collection, data preprocessing, implementation of the K-Means algorithm, evaluation of cluster quality using the Davies-Bouldin Index (DBI), validation of the chosen number of clusters using the Elbow method, the DBI, and cluster size, analysis and interpretation of the clustering results, and the formulation of inventory management recommendations. Data extraction was performed using Tabula and data preprocessing using Microsoft Excel. The K-Means implementation, the Elbow and DBI calculations, and the cluster quality evaluation were performed in RapidMiner, and the Elbow curve was plotted in Microsoft Excel.

2.1 Data Collection

The data used in this study were obtained through interviews, observations, and documentation at Fahra Jaya Store. Interviews were conducted to gather general information about sales activities, observations were conducted to directly observe the ongoing sales process, and documentation was used to obtain historical sales transaction data, which served as the primary data for the analysis. The collected data consisted of sales transaction reports in PDF format covering a ten-month period, from January through October 2025. From this period, a total of 1,550 raw sales transaction records were obtained. The entire dataset or population was used in the study by applying total sampling, meaning that the entire dataset was used without selecting a subset as a sample. These raw sales transaction records contained several attributes: item code, product name, number of units sold, and transaction period.

Before preprocessing, the data kept the original structure of the store's transaction reports, in which each record shows a product and its sales volume for a specific transaction period. Table 1 gives an example,

using records from the early, middle, and late parts of the January–October 2025 period to show the structure of the data collected during the study.

Table 1. Sample of Raw Sales Transaction Data Before Preprocessing

No.	Item Code	Product Name	Number of Units Sold	Transaction Date
1	sabun0104	Mama jeruk nipis 120ml	5.00 PCS	01/01/2025
2	minuman147	Kapal api 6.5gr	1.00 rtng	01/02/2025
3	sampho01	Sunsilk black shine 9ml	1.00 rtng	01/05/2025
4	ROKOK0157	Grow berry bold 16	1.00 PCS	01/06/2025
5	makanan334	Expreso kopi susu	1.00 PCS	01/09/2025
6	makanan0695	Telor 1kg	5.00 Kg	01/10/2025
…	…	…	…	…

Source: Fahra Jaya Store sales transaction data, 2026

As Table 1 shows, the raw data are unprocessed records taken directly from the store's reports. They therefore go through several preprocessing steps (extraction, cleaning, integration, selection, transformation, and normalization) to produce a dataset suitable for K-Means analysis [15].

2.2 Data Preprocessing

Before being used in the clustering process, the sales transaction data must first undergo a preprocessing stage. This stage includes extraction, cleaning, integration, selection, transformation, and data normalization. The process begins by extracting the transaction reports which were originally in PDF format into CSV format for each period from January through October 2025 using the Tabula application. The extracted data is then cleaned to ensure consistency in table structure, column names, and data format. To simplify the data and avoid duplicate entries, transactions for similar products in the same month are consolidated using the PivotTable feature in Microsoft Excel. This step aimed to consolidate the number of units sold for each product into a single data row, the cleaned data was then saved as separate files for each month.

After the monthly data was neatly organized, all the files were integrated into a single, complete dataset using the Append Queries feature in Power Query within Microsoft Excel. Next, attributes relevant to the analysis objectives namely, product name, number of units sold, and transaction period were selected. The data for the selected attributes were then transformed to form the three main research variables: number of units sold, average sales, and sales growth. These three variables were used to describe the characteristics of product sales, both in terms of volume and growth over time [12], [13]. The definitions and calculations for each variable are presented in Table 2.

Table 2. Definitions and Calculations of Research Variables

No.	Variable	Definition	Calculation
1	Number of units sold	Total number of product units sold from January through October 2025	Σ Sales
2	Average sales	Average number of product units sold each month during the study period	$\bar{x} = \frac{\sum x_i}{n}$
3	Sales growth	Change in sales for the current period compared to the previous period	$SG = \frac{Sales_m - Sales_{m-1}}{Sales_{m-1}}$
		Average Sales Growth	$\overline{SG} = \frac{1}{9}\sum_{m=Feb}^{Oct} SG_m$

Source: Adapted from [12], [16], [13]

According to Table 2, the number of units sold is the total sales of each product from January through October 2025, and average sales is that total divided by the ten months of observation. Sales growth was calculated for each pair of consecutive months from February to October 2025 using the formula in Table 2, which gives nine monthly growth values for each product. The nine monthly values were then averaged into one average sales growth value for each product, which became the third variable in the clustering process [12], [16], [13].

Table 3. Example of Monthly Sales and Growth Calculation

Month.	Beras Rojo Lele1kg (Unit sold)	Growth	Average Sales Growth
Jan	466	-	
Feb	421	-9.66%	
Mar	165	-60.81%	
Apr	198	20.00%	
May	121	-38.89%	16.87%
Jun	390	222.31%	
Jul	562	44.10%	
Aug	601	6.94%	
Sep	508	-15.47%	
Oct	423	-16.73%	

Source: Author's processing using Microsoft Excel, 2026

Table 3 presents an example of monthly sales and growth calculation for Beras Rojo Lele 1kg. Monthly growth is calculated as the difference between sales in the current month and the previous month, divided by sales in the previous month. Sales decreased from 466 units in January to 421 units in February, resulting in a growth rate of (421 − 466) / 466 × 100% = −9.66% for February. By averaging the nine monthly growth rates from February to October, the average sales growth is obtained as 16.87%, which is the value used for this product in the clustering process (Table 4).

After the three research variables were established, the next step involved normalization using the Min-Max Normalization method to standardize the variable values within the range of 0 to 1, in order to prevent large-valued variables from dominating the distance calculations in the K-Means algorithm [8]. The normalization process was calculated in Microsoft Excel using Equation 1 [8]. The minimum and maximum values used were 1 and 3,855 for number of units sold, 0.1 and 385.5 for average sales, and −59.60% and +666.36% for sales growth.

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

In Equation 1, x' represents the normalized value, x represents the original data value, while x_{min} and x_{max} represent the minimum and maximum values for each variable, respectively. The normalized data is then used as input in the K-Means clustering process.

2.3 K-means Implementation

The K-Means algorithm was selected as the clustering method to group data into several clusters based on the similarity of their characteristics, by repeatedly calculating the distance of each data point to the cluster center (centroid) until the centroid positions stabilize [17]. In this stage, the three variables formed during preprocessing (number of units sold, average sales, and sales growth) are used as input, after Min-Max normalization to a uniform 0–1 range.

The clustering process followed the standard K-Means steps [18]. The number of clusters was set to three (k = 3) based on domain knowledge [19], [8], and on the inventory needs of Fahra Jaya Store: the owner needs to separate products to maintain, to increase gradually, and to evaluate [5]. Because this study aims at sales patterns that support inventory decisions rather than at the mathematically optimal k, this practical need guided the initial choice. To test whether the data also support it, the results for k = 2 to 6 were compared using the Elbow method, the Davies-Bouldin Index (DBI), and the number of products in each cluster, as described in Section 2.5.

Initial centroids were selected by RapidMiner as reference points for the first iteration. The distance between each product and each centroid was then calculated as the Euclidean distance on the three normalized variables, using Equation 2 [18].

$$D_{ik} = \sqrt{(X_{1i} - C_{1k})^2 + (X_{2i} - C_{2k})^2 + (X_{3i} - C_{3k})^2} \quad (2)$$

In Equation 2, D_{ik} is the distance of the i-th product from the centroid of the k-th cluster. X_{1i}, X_{2i}, and X_{3i} represent the number of units sold, average sales, and sales growth of the i-th product, while C_{1k}, C_{2k}, and C_{3k} are the values of the centroid of the k-th cluster for each attribute. The resulting distance values are then used to determine the cluster membership of each product.

Each product is then assigned to the cluster with the smallest distance, and the centroid of each cluster is updated as the average of its members using Equation 3 [18].

$$v_{ij} = \frac{1}{N_i} \sum_{k=1}^{N_i} x_{kj} \quad (3)$$

In Equation 3, v_{ij} is the centroid value of the i-th cluster for the j-th attribute, N_i is the number of data points belonging to the i-th cluster and x_{kj} is the value of the k-th data point for the j-th attribute within that cluster.

The updated centroid values are then compared with the centroids from the previous iteration. If changes still occur, the clustering process is repeated until stable centroid values are obtained or convergence is reached. K-Means was run in RapidMiner with $k = 3$. The initial centroids were set with the 'determine good start values' option, using a maximum of 10 runs and keeping the best result; the local random seed option was not enabled. Each run stopped when the centroids stabilized or after 100 optimization steps. Distance was measured with Mixed Euclidean Distance, which equals the Euclidean distance in Equation 2 because all three attributes are numerical.

2.4 Cluster Quality Evaluation

After the clustering process is complete, cluster quality was evaluated using the Davies-Bouldin Index (DBI), which looks at how compact the members of each cluster are and how well the clusters are separated from one another [20]. The smaller the DBI, the closer it is to zero, the better the clustering result [21]. The DBI is calculated using Equation 4 and was obtained from the Performance (Cluster Distance Performance) operator in RapidMiner which was used to assess the quality of the clustering results [20].

$$DBI = \frac{1}{k} \sum_{i=1}^{k} \max_{j \neq i} (R_{ij}) \quad (4)$$

In Equation 4, k is the number of clusters and R_{ij} is the similarity ratio between cluster i and cluster j, calculated as $(S_i + S_j) / D_{ij}$. Here, S_i is the average distance between the members of cluster i and its centroid (the within-centroid values in Table 7 are squared distances), and D_{ij} is the distance between the centroids of clusters i and j. Each cluster is compared with the cluster most similar to it (the largest R_{ij}), and these values are averaged over all clusters.

2.5 Validation of the Number of Clusters

Because $k = 3$ was set from domain knowledge, a separate check was needed to see whether the data also support it. For this purpose, the Elbow method was used. It selects the number of clusters at the point where the drop in data spread begins to level off and forms an "elbow". This spread is commonly measured by the Sum of Squared Errors (SSE) [22]. RapidMiner, however, provides a comparable measure for the same purpose, the Average Within-Centroid Distance (AWCD), which is the average squared Euclidean Distance between each product and the centroid of its cluster [23], [24].

K-Means was then run in RapidMiner Studio for k = 2 to 6 with identical parameters, so that only the number of clusters changed. Each result was evaluated with the Cluster Distance Performance operator to obtain the AWCD and DBI values [24]. The AWCD values for each k were then plotted in Microsoft Excel to form the Elbow curve. Cluster sizes were checked as well, because the lowest DBI is not always the best result: a small cluster of a few extreme products can lower the DBI even though it more likely represents outliers than a sales pattern [25], [26]. When the three criteria point to different values of k, the decision rests on the balance between clustering quality and ease of interpretation for inventory needs, not on statistics alone [26].

2.6 Analysis and Interpretation of Results

Once the clustering and evaluation were complete, the results were analyzed using the number of members in each cluster, the final centroid values, and the Davies-Bouldin Index (DBI). Because the final centroids are normalized values, they were converted back to the original scale by reversing the Min-Max normalization in Equation 1, so that each cluster could be described in actual sales terms (units sold, units per month, and percent growth per month). For each cluster, the converted mean and the median of these original values were compared, together with its share of all units sold and the variation among its members (the standard deviation of growth and the coefficient of variation of monthly sales), as presented in Table 9. From these values, each cluster was described as high, moderate, or low in sales and growth, and this description

became the basis for the inventory recommendations for Fahra Jaya Store: maintain, increase gradually, or evaluate stock (Section 3.5).

3. RESULTS AND DISCUSSION

This section presents the results of applying the K-Means algorithm to sales transaction data from Fahra Jaya Store to group products according to sales volume and sales growth. The results are organized into several stages, beginning with data preprocessing and the implementation of K-Means with $k = 3$. The quality of the clustering results is then evaluated using the Davies-Bouldin Index (DBI), followed by validation of the selected number of clusters through a comparison of solutions with different values of k. Finally, the characteristics of the resulting clusters are examined to formulate inventory management recommendations.

3.1 Dataset After Preprocessing

The raw dataset contained 1,550 sales transaction records from Fahra Jaya Store covering January to October 2025. The data were extracted using Tabula and organized by month in Excel. Records of the same product sold on different days within a month were combined, and quantity values were converted to numeric format for calculation using PivotTables. After data processing, 1,003 product records were obtained. Three variables were then selected: number of units sold, average sales, and sales growth, representing sales volume, average monthly sales, and changes in sales over time, respectively [12], [16], [13]. Table 4 presents examples of the data before and after normalization.

Table 4. Preprocessed Dataset and Normalized Data Results

No.	Product Name	Number of Units Sold	Average Sales	Sales Growth	Number of Units Sold (Normalized)	Average Sales (Normalized)	Sales Growth (Normalized)
1	Beras rojo lele1kg	3,855	385.5	16.87%	1	1	0.105
2	Cho-cho crispy 12pcsx9g	12	1.2	-38.89%	0.003	0.003	0.029
3	Beras rojo lele 25kg	138	13.8	49.13%	0.036	0.036	0.150
4	Oishi pillow coklat	13	1.3	-20.63%	0.003	0.003	0.054
5	Abc terasi udang84gr	97	9.7	30.12%	0.025	0.025	0.124
6	Sari gandum coklat 39gr	15	1.5	-28.40%	0.004	0.004	0.043
7	Abc sambel extra pedas 8gr	120	12	10.28%	0.031	0.031	0.096
8	Ekomie isi 3x120gr	190	19	-8.75%	0.049	0.049	0.070
…	…	…	…	…	…	…	…

Source: Author's processing using Microsoft Excel, 2026

Across the 1,003 products before normalization, the raw values vary widely. Total units sold range from 1 to 3,855, average sales range from 0.1 to 385.5, and average monthly sales growth ranges from −59.60% to +666.36%. Since average sales is calculated by dividing total units sold by ten months, the two variables have the same normalized values, as shown in Tables 4. Normalization scales all three variables to a range of 0 to 1, so that no variable dominates the distance calculation because of its unit.

3.2 Results of the K-Means Clustering Implementation in RapidMiner

The K-Means implementation was performed on the preprocessed dataset consisting of three variables used as attributes: number of units sold, average sales, and sales growth. This process was run using RapidMiner to generate product clusters, centroid values, and an evaluation of cluster quality via the Davies-Bouldin Index (DBI). All of these steps were organized into a single workflow (design process) with a series of interconnected operators. This design process is shown in Figure 1.

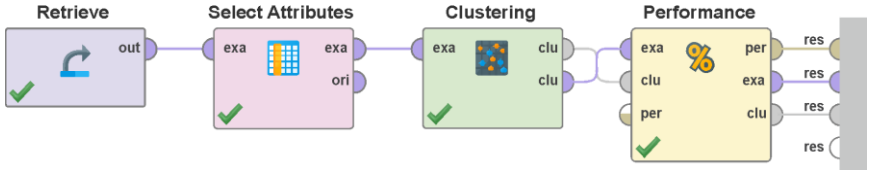


Figure 1. RapidMiner Design Process
Source: Author's processing using RapidMiner, 2026

As shown in Figure 1, the RapidMiner process consists of four interconnected operators: Retrieve, which loads the dataset containing 1,003 product records; Select Attributes, which selects the numerical attributes used for clustering; Clustering, which applies the K-Means algorithm with (k = 3), automatic determination of good starting values, and a maximum of 100 optimization steps; and Performance, which uses

the Cluster Distance Performance operator to evaluate the clustering results based on within-cluster distances and the Davies-Bouldin Index (DBI).

After the workflow was executed, RapidMiner generated an ExampleSet in which each product is labeled with its cluster, as shown in Table 5.

Table 5. RapidMiner Clustering Results ExampleSet

Id	Cluster	Number of Units Sold	Average Sales	Sales Growth
1	Cluster_0	1	1	0.105
2	Cluster_2	0.003	0.003	0.029
3	Cluster_2	0.036	0.036	0.150
4	Cluster_2	0.003	0.003	0.054
5	Cluster_2	0.025	0.025	0.124
6	Cluster_2	0.004	0.004	0.043
…	…	…	…	…

Source: Author's processing using RapidMiner, 2026

In Table 5, each product has been assigned to Cluster 0, Cluster 1, or Cluster 2 according to the similarity of its characteristics. Table 6 shows number of products in each cluster and the final centroid values.

Table 6. Cluster Size and Final Centroid Values in RapidMiner

Cluster	Number of Products	Number of Units Sold	Average Sales	Sales Growth	Total Number of Products
0	31 Products	0.236	0.236	0.101	
1	93 Products	0.027	0.027	0.266	1,003
2	879 Products	0.012	0.012	0.079	

Source: Author's processing using RapidMiner, 2026

Based on Table 6, a total of 1,003 products were successfully grouped into three clusters using K-Means (k = 3) in RapidMiner with a maximum of 100 optimization steps. Cluster 2 is by far the largest, containing 879 products (87.6%), and has the lowest centroid values on all three attributes. Cluster 1 contains 93 products (9.3%) and has the highest sales growth (0.266), while its number of units sold and average sales remain low (0.027). Cluster 0 is the smallest, with 31 products (3.1%), but has the highest number of units sold and average sales (0.236), with a sales growth (0.101) that falls between those of the other two clusters. A more detailed interpretation of each cluster on the original scale is presented in Section 3.4 (Table 9).

Figure 2 shows how the members of each cluster are distributed over the three attributes in a 3D scatter plot.

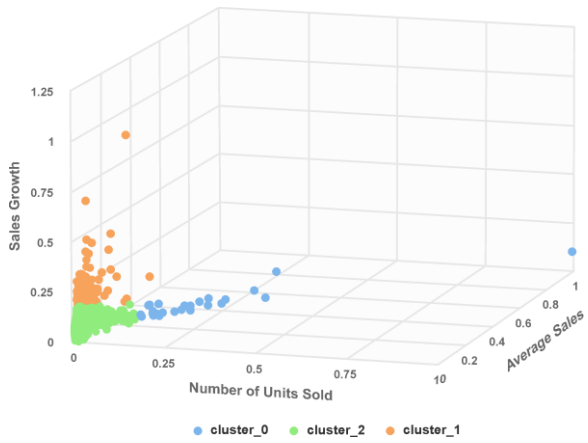


Figure 2. 3D Scatter Visualization of K-Means Clustering Results
Source: Author's processing using RapidMiner, 2026

Based on Figure 2, Cluster 0 (blue) consists of products with higher units sold and average sales, Cluster 1 (orange) occupies the area with relatively higher sales growth, and Cluster 2 (green) is concentrated at low values on all attributes. This shows that the clustering separated the three product characteristics.

The resulting clusters were then evaluated using the Davies-Bouldin Index (DBI) via the Performance operator in RapidMiner. The evaluation results were used to measure the quality of the clustering based on the levels of compactness and separation between clusters [20]. The DBI evaluation results are presented in Table 7.

Table 7. Results of the Davies-Bouldin Index Evaluation in RapidMiner

Metric	Cluster 0	Cluster 1	Cluster 2	Overall
Avg. within-centroid distance (Squared Euclidean)	0.050	0.015	0.002	0.005
Davies-Bouldin Index (DBI)	-	-	-	0.638

Source: Author's processing using RapidMiner, 2026

Table 7 shows the average squared distance to the centroid, which describes how widely the members of each cluster are spread. Cluster 0 has the highest value (0.050), even though it has only 31 products, which shows that its members are widely dispersed. Cluster 1 has a moderate value (0.015), and Cluster 2 has the lowest value (0.002), meaning that its 879 products are close to the cluster center and have similar sales characteristics. Based on these values, the DBI was 0.638, with lower values indicating better compactness and separation [21]. By itself, however, this value does not show whether three is a sensible number of clusters, so it is compared with other values of k in the next section.

3.3 Validation of the Number of Clusters

To check whether $k = 3$ holds up against the alternatives, K-Means was run again with $k = 2$, 4, 5, and 6 on the same normalized data and parameters. Table 8 shows the AWCD, the DBI, and the number of products in each cluster for every value of k, and Figure 3 plots the Elbow curve and the DBI side by side.

Table 8. Comparison of Cluster Solutions for $k = 2$ to 6

k	AWCD	DBI	Number of products in each cluster	Smallest cluster
2	0.007	1.114	861; 142	142
3	**0.005**	**0.638**	**879; 93; 31**	**31**
4	0.004	0.494	866; 94; 42; 1	1
5	0.002	0.572	614; 315; 41; 32; 1	1
6	0.002	0.591	551; 334; 74; 34; 9; 1	1

Source: Author's processing using RapidMiner, 2026

Note: AWCD = average within-centroid distance (average squared Euclidean distance), rounded to three decimals. Cluster sizes are sorted from largest to smallest.

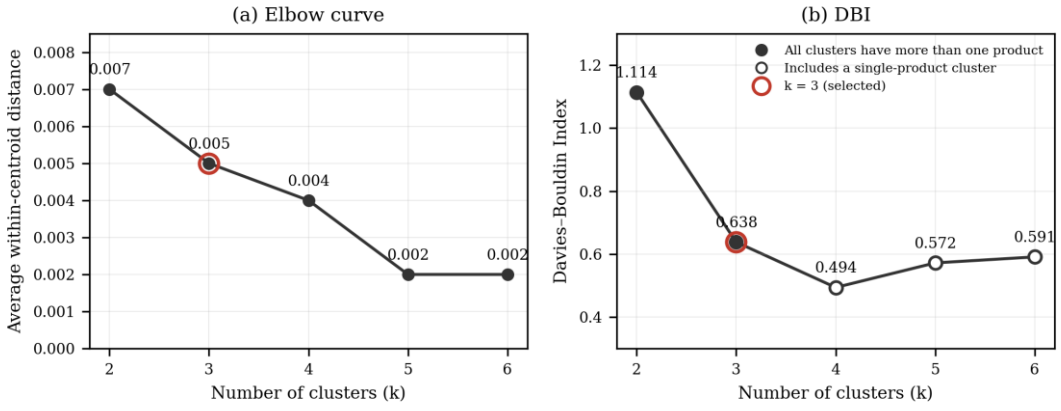


Figure 3. Elbow Curve (a) and Davies–Bouldin Index (b) for $k = 2$ to 6

Source: Author's processing using RapidMiner and Microsoft Excel, 2026

The elbow curve in Figure 3(a) decreases gradually without showing a sharp bend. The AWCD value decreases from 0.007 at $k = 2$ to 0.005 at $k = 3$, then to 0.004 at $k = 4$, and remains stable at 0.002 for $k = 5$ and $k = 6$. Because the AWCD values change by very small amounts at three decimals , the Elbow curve cannot confirm an optimal k and is used only as supporting evidence. Therefore, the DBI values and cluster sizes must also be considered [26].

The DBI values in Figure 3(b) provide a clearer picture [23], [25], [26]. The DBI value decreases from 1.114 at k = 2 to 0.638 at k = 3, and reaches its lowest value of 0.494 at k = 4. It then increases to 0.572 at k = 5 and 0.591 at k = 6. Although k = 4 has the lowest DBI value, the cluster sizes in Table 8 show that at k = 4, there is one cluster that contains only a single product, while the other three clusters (866, 94, and 42 products) are nearly identical to the three clusters at k = 3 (879, 93, and 31 products). This indicates that the addition of a fourth cluster does not result in a new group of products with its own sales pattern. That single product is "Beras Rojo Lele 1kg" which is the best-selling product but is separated into a different cluster because both attributes (number of units sold and average sales) have a normalization result of 1. In cluster-based outlier detection, outliers are typically represented as points that do not belong to any cluster [25]. Consequently, this cluster containing only one product is classified as an outlier rather than a meaningful product group.

The lower DBI at k = 4 is largely due to one product being placed in a separate cluster. As shown in Table 4, Beras Rojo Lele 1 kg has normalized values of 1 for both units sold and average sales, well above the Cluster 0 centroid of 0.236 for both variables (Table 6). This contributes to the high within-cluster distance of Cluster 0 in Table 7 (0.050). After being separated, this product forms a cluster of its own, making the remaining products more closely grouped and lowering the DBI [26]. k = 5 and k = 6 also each contain a one-product cluster. Therefore, the number of clusters should not be selected based on statistical values alone. The clustering results should also support inventory rules that the store can apply in practice [26].

For this study, k = 3 is a suitable choice for the store's inventory needs. At this value, the DBI decreases to 0.638, showing a clear improvement over k = 2, while the Elbow curve does not show a clear bend at any k value. Although the DBI is lowest at k = 4, all larger values of k produce a cluster containing only one product, making them less useful for practical inventory decisions. In contrast, k = 3 produces three clusters with enough products to support different inventory actions. Two clusters may not distinguish sales patterns in enough detail, while five or six clusters would make inventory management more complicated. Therefore, k = 3 is not claimed to be the mathematical optimum but is considered a reasonable choice based on the clustering results and the store's practical needs.

3.4 Analysis and Interpretation of Clustering Results

Based on Table 6 presented in Section 3.2, the results of the K-means implementation with k = 3 on the attributes of number of units sold, average sales, and sales growth reveal the characteristics of each cluster based on the different final centroid values for each cluster. Cluster 0 has the highest values for total units sold and average sales; Cluster 1 has the highest value for sales growth; while Cluster 2 has the lowest values for all three attributes.

Although these final centroid values were obtained, they are normalized values, making them difficult to interpret and understand. Therefore, Table 9 converts the final centroids back to their original scale (mean units sold, average sales, and average monthly growth). Because the centroids in Table 6 are rounded to three decimals, the conversion uses the unrounded values, so it can differ slightly from a manual conversion of Table 6. Table 9 also reports the median, the share of all units sold, and the variation within each cluster (SD and CV), which are calculated directly from the original data of the products in each cluster.

Table 9. Cluster Profiles on the Original Scale

Cluster	Products (%)	Units sold Jan–Oct: mean (median)	Avg. monthly sales (units/month)	Avg. monthly growth, mean (median%)	SD of avg. growth across products (pp)	Share of all units sold	CV	Characteristics
0	31 (3.1%)	910.5 (666)	91.1	+13.76% (+5.71%)	20.83	35.0%	0.37	High sales, moderate growth (moderate trend)
1	93 (9.3%)	105.9 (77)	10.6	+133.42% (+107.30%)	86.02	12.2%	0.91	Low sales but high growth (upward trend)
2	879 (87.6%)	48.3 (18)	4.8	−2.61% (−8.80%)	25.68	52.7%	1.17	Low sales and growth (low trend)

Source: Author's processing using RapidMiner and Microsoft Excel, 2026

Note: Means are the final centroids converted back with $x = x_{norm} \times (x_{max} - x_{min}) + x_{min}$ [8], using unrounded centroid values; x_{min} and x_{max} are 1 and 3,855 (units sold), 0.1 and 385.5 (average sales), and −59.60% and +666.36% (growth). SD is the sample standard deviation of the products' average monthly

growth within each cluster, in percentage points (pp). CV = coefficient of variation of monthly sales (median across the products in each cluster)

On the original scale (Table 9), Cluster 0 contains 31 products (3.1% of all products) with the highest sales. These products sold an average of 910.5 units over the ten months (91.1 units per month), and half of these products sold 666 units or fewer. Even though this group is small, these products contribute 35.0% of all units sold. Its average monthly growth is +13.76% (median +5.71%), which is moderate compared with Cluster 1 (+133.42%) and Cluster 2 (−2.61%). Moderate growth does not mean that sales never go down. For example, Beras Rojo Lele 1kg, the best-selling product, sold between 121 and 601 units per month, with monthly growth ranging from −60.81% to +222.31% (Table 3). Even so, monthly sales in this cluster vary less than in the other clusters, with a median CV of 0.37 compared with 0.91 for Cluster 1 and 1.17 for Cluster 2 (Table 9). Based on these values, Cluster 0 is categorized as the cluster with high sales and moderate growth. Because these few products make up about a third of all units sold, and the sales of these product can still go up or down from month to month, the store should maintain stock availability for these products, using safety stock and a reorder point (Section 3.5).

Cluster 1 contains 93 products (9.3% of all products) with low sales but high growth. These products sell an average of 10.6 units per month, and half of these products sold 77 units or fewer over the ten months. Together these products account for only 12.2% of all units sold. The average monthly growth is +133.42% (median +107.30%), the highest of the three clusters and far above Cluster 0 (+13.76%) and Cluster 2 (−2.61%). The high percentages mainly reflect the small sales base, since an increase of only a few units per month already produces a large percentage. The mean (+133.42%) is also higher than the median (+107.30%), which suggests that a few products grew much faster than the rest. Growth differs widely among these products (standard deviation of 86.02 percentage points, the largest of the three clusters, compared with 20.83 for Cluster 0 and 25.68 for Cluster 2). Because of this wide spread, the median is a more typical value for this cluster: half of these products had an average monthly growth of +107.30% or lower. Based on these values, Cluster 1 is categorized as the cluster with low sales and high growth (upward trend). Since high growth does not guarantee that sales will keep rising at the same pace, the store should increase stock gradually, and only while sales of these products keep rising.

Meanwhile, Cluster 2 is the largest group, with 879 products (87.6% of all products), and this cluster has the lowest values on all three clustering variables. These products sold an average of 48.3 units over the ten months (4.8 units per month), and half of of these products sold 18 units or fewer. Average monthly growth is −2.61% (median −8.80%). Both values are negative, so sales in this group are on average flat to slightly declining. This does not apply to every product, however: growth varies from product to product (standard deviation of 25.68 percentage points), so some products in this cluster may still be growing. Although each product sells only a little, together these products account for 52.7% of all units sold, more than half of the total, so this cluster cannot simply be ignored. Based on these values, Cluster 2 is categorized as the cluster with low sales and growth (low trend). For this reason, the store should evaluate these products one by one before deciding whether to reduce stock, rather than cutting stock across the whole cluster.

The clustering results show that, when sales growth is taken into account, product groups become easier to distinguish than when sales volume alone is used. Cluster 0 has high sales and moderate growth, Cluster 1 has low sales but high growth, and Cluster 2 has the lowest sales and growth. If only sales volume were used, Cluster 1 would appear similar to Cluster 2, since both have low sales, and products that are rising would appear the same as products that are falling based on their growth rates. Therefore, growth fills that gap: the two clusters are distinguished primarily by their average growth rates (+133.42% versus −2.61%), even though Cluster 1 also sells more (an average of 105.9 units versus 48.3 units over the ten months) [13], [14].

This is where this study differs from previous research. Yahya and Kurniawan [9] grouped 30 food sales records into two clusters: 21 best-selling products and 9 least popular products. Damayanti and Putri [10] divided rice sales into three categories; unpopular, popular, and very popular with final centroids of 284.62, 730, and 1,300 kg. In both of those studies, the clustering mainly indicated how much of each product was sold. Meanwhile, although Bozanta et al. [11] grouped products based on sales patterns over time, their method relies on large daily time-series datasets and custom distance metrics.

In contrast, this study clusters 1,003 products using units sold, average sales, and sales growth. Because growth is included, products with similar low sales can be distinguished: products that are growing (Cluster 1) and products that are stagnant or declining (Cluster 2). Additionally, the appropriate choice of k is validated using the Elbow Method and by comparing the number of clusters.

3.5 Inventory Management Recommendations

The cluster profiles in Table 9 show that each product group has a different sales pattern, so inventory management should not be applied uniformly. The recommendations for Fahra Jaya Store were therefore formulated for each cluster (Table 10) using two inventory concepts.

ABC classification gives closer control to products that contribute most to sales value [27], [28], while safety stock is extra inventory that covers unexpected demand, and the reorder point (ROP) indicates when a new order should be placed [27]. Because the clusters in this study are based on units sold and growth rather than sales value, they are not treated as ABC classes; the concept is used only to support closer attention to products with a large sales contribution. Using average monthly demand D, its standard deviation σ, lead time L (in months), and a safety factor z, safety stock is $SS = z \times \sigma \times \sqrt{L}$ [29] and $ROP = D \times L + SS$ [28].

Table 10 gives a simple action for each cluster, with example products. Cluster 0 (high sales, moderate growth) should be maintained. It contains only 3.1% of the products but accounts for 35.0% of the units sold, so keeping stock available is the priority. Safety stock and a reorder point are recommended, together with regular stock checks. Cluster 1 (low sales, high growth) should be increased gradually. It contains 9.3% of the products but accounts for only 12.2% of the units sold, and its high growth rates may result from small sales quantities. Orders are therefore raised step by step, and only while sales keep rising, to avoid overstock. Cluster 2 (low sales and growth) should be evaluated product by product rather than reduced as a whole, since it still accounts for 52.7% of the units sold. Orders are reduced only for products with continued declines and sufficient remaining stock, while products with a short shelf life are checked near their expiry date [27].

Table 10. Examples of Products in Each Cluster and Inventory Management Recommendations

Cluster	Example products	Sales characteristics	Recommended action
0	Beras rojo lele 1kg Gula pasir 1kg Sedap mie goreng 90gr Beras dua jago 1kg Indomilk kids coklat115 Jumbo kingkong 1pak … Kapal api special mix 10x23gr	High sales, moderate growth	Maintain stock: keep stock available and check it regularly; set safety stock and reorder point based on demand and lead time
1	Mama lemon 58ml Sedap kecap manis 60ml Clevo strawberry125ml Kacang atom bledug 70gr Roma kelapa 300gr Slop foam kecil 1pcs … Miwon 50gr	Low sales, high growth	Increase gradually: monitor sales and raise orders step by step only if growth continues; avoid large orders based on growth percentage alone
2	Gudang garam surya coklat 12 Mama jeruk nipis 120ml Royco rasa ayam 8gr Kecap sedap 63ml Indocafe coffeemix 3in1 20g Indofood kecap manis 60ml …	Low sales and growth	Evaluate: review each product before reducing orders; reduce only with continued decline and sufficient stock; check expiry for short shelf-life products

Source: Author's analysis based on the clustering results and inventory theory [27], [28], [29], 2026

As an illustration, for Beras Rojo Lele 1kg (Cluster 0), the average monthly demand D is 385.5 units (Table 4), and σ, the standard deviation of its monthly sales (a measure of how much sales fluctuate), can be calculated from the ten monthly figures in Table 3. The lead time L (how long a new order takes to arrive) and the safety factor z (how much protection against stockouts the owner wants) are not part of the sales data, so the store owner has to set them. Because safety stock is calculated from past sales fluctuation, how reliable it is depends on how well past sales describe demand during the lead time [29]. The result should therefore be treated as a starting point, and the owner should adjust it to actual lead times, stockouts, storage capacity, and shelf life, and re-run the clustering periodically so that products can be moved to a different action when their sales change.

4. CONCLUSIONS

This study applied the K-Means Clustering algorithm to group products at Fahra Jaya Store based on their sales patterns, using historical sales transaction data from January through October 2025. The clustering was performed using three variables: number of units sold, average sales, and sales growth. A total of 1,003 products resulting from preprocessing were successfully grouped into three clusters with distinct sales characteristics. The number of clusters was set from the inventory needs of the store and then compared with $k = 2$ to 6 using the Elbow method, the Davies-Bouldin Index (DBI), and cluster size. The Elbow curve declined

gradually without clear bend, so it could not show which number of clusters is best. The DBI was lowest at $k = 4$ (0.494). However, the extra cluster at $k = 4$ contained only one product, and every larger k also produced a single-product cluster, so a lower DBI did not mean more useful groups [25]. With $k = 3$, the DBI was 0.638, clearly better than the 1.114 obtained with $k = 2$. For these reasons, three clusters were kept as a practical choice for this study rather than as a mathematically optimal number [21].

The clustering results show that Cluster 0 (31 products) consists of products with high sales and moderate growth (average growth of +13.76% per month), Cluster 1 (93 products) contains products with the highest sales growth among the three clusters (average growth of +133.42% per month, from a small sales base) and has the potential for increased demand, while Cluster 2 (879 products) is dominated by products with relatively low sales levels and low growth, slightly negative on average (−2.61% per month).

The application of the K-Means algorithm in this study provides information that can serve as the basis for more targeted and data-driven inventory management decisions. Through the results of product clustering, store owners can apply a different action to each group: maintain stock for Cluster 0 using safety stock and reorder points, increase stock gradually for Cluster 1, and evaluate products one by one before reducing stock for Cluster 2.

However, this study still has limitations because it only uses historical sales data and three research variables as the basis for the clustering process. Other factors, such as promotions, sales seasons, price changes, and consumer preferences, have not been considered in the clustering process; therefore, it cannot yet account for all factors influencing product sales patterns.

Another limitation concerns sales growth. Because it is the average of monthly percentage changes, a small sales base can produce very large percentages, as in Cluster 1, whose average growth of +133.42% per month comes from a mean of only 10.6 units per month (Table 9).

A further limit is that average growth measures the direction of sales, not their stability, so Cluster 0 is described by moderate growth rather than by stable sales. Finally, the inventory actions in Table 10 combine the cluster profiles with standard inventory theory but have not yet been tested in the store.

Future research is recommended to use a longer data period, incorporate variables related to both internal and external sales factors, and compare the K-Means algorithm with other clustering methods to obtain more comprehensive clustering results. Other validity measures, such as the Silhouette coefficient, and repeated runs with different random initializations could also be used to test how stable the chosen number of clusters is. Sales stability, such as the coefficient of variation of monthly sales, could also be added as a clustering variable, since in this study it is used only to describe the clusters (Table 9). The recommended actions in Table 10 could also be evaluated by comparing stockout and overstock rates before and after the store applies them.

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