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Demand-Based Product Classification Using K-Means with Intermittency Metrics

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Abstract
Inventory management at multi-SKU distribution companies becomes complex when most products have unstable and intermittent demand patterns. At PT JJA, procurement is still reactive without the use of historical patterns, while the previous approach generally relied on aggregate indicators such as average sales so that it has not been able to comprehensively capture temporal dynamics. This study aims to group products based on temporal demand patterns using K-Means Clustering in 11,988 transactions for the 2020–2025 period which are processed into 261 products through monthly aggregation, with features of average sales, coefficient of variation (CV), zero_month_ratio, Average Demand Interval (ADI), and trends. The results showed four optimal clusters (k = 4) with a Silhouette Score of 0.62 and an unbalanced distribution, where one cluster dominated 240 products. The values of zero_month_ratio (>0.80), ADI up to >12 months, and CV up to >3.5 show intermittent demand patterns and long-tail structures. The study confirms that the integration of temporal features (ADI, zero_month_ratio, CV, and trend) transforms the representation of demand from static aggregates to dynamic structures, while linking segmentation results with more adaptive procurement strategies to reduce the risk of overstock and understock.

Keywords: k-means clustering; product segmentation; procurement of goods

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INTRODUCTION

Inventory management on a multi-SKU system faces complexity when the majority of products exhibit intermittent and unstable demand patterns. This condition often leads to improper procurement decisions, such as overstock on products that are rarely sold and stock shortages on the products needed. These differences in characteristics make a uniform management approach less than optimal in practice (Wisner et al., 2023). As well as having an impact on excess stock that binds working capital and running out of stock which reduces customer satisfaction (Heizer et al., 2023). Therefore, an approach that is able to group products based on demand characteristics is needed that is more representative. However, there is no consensus in the literature on the most appropriate indicators to represent simultaneous intermittent demand patterns on multi-SKU systems.

Product demand on a multi-SKU system is generally not constant, but rather shows temporal patterns such as fluctuations, trends, and no-sales periods. This condition reflects intermittent demand that is difficult to capture using conventional aggregate-based approaches.

Although methods such as K-Means are computationally effective, the use of aggregate features such as sales averages has the potential to eliminate the time dimension, making interpretations of product characteristics biased (Kolassa et al., 2023; Sanguri et al., 2024). This condition often leads to improper procurement decisions, such as overstock on products that are rarely sold and stock vacancies on the products needed. This problem is also reinforced by the finding that traditional forecasting methods that ignore temporal dynamics tend to result in inaccurate predictions and suboptimal inventory decisions (Wang & Ning, 2026; Wang & Minner, 2024).

PT JJA still implements a reactive procurement pattern (make to order) without the support of systematic demand prediction, even though historical sales data stores important information related to demand patterns. To overcome this, this study uses an unsupervised learning-based data mining approach with the K-Means Clustering algorithm to group products based on the similarity of demand characteristics. This method was chosen because it is efficient for large-scale data, although it has limitations such as sensitivity to centroid initialization and clister count determination (Pramudya et al., 2026), and applied to support decision-making based on unstable demand patterns (Ezugwu et al., 2023). However, the use of K-Means in the previous literature is still generally limited to aggregate data-based grouping or static features, so it has not fully explored the temporal character of requests in the context of multi-SKUs.

While previous study has emphasized the use of machine learning and clustering techniques in demand analysis and supply chain management, existing approaches still tend to be partial in accommodating temporal dynamics comprehensively. A study by Giannopoulos et al. (2023) It is still at the level of general model synthesis without the specification of operational temporal features, so methodologically it does not provide guidance for the representation of time-based data and has implications for segmentation that is less sensitive to temporal variations. On the other hand Tarragó et al. (2023), use temporal data in a homogeneous context, which limits its methodological scope and has implications for low generalizations to heterogeneous multi-SKU systems. Further, Keskin and Taşkın (2024) Develop an artificial intelligence-based inventory classification at a conceptual level without formulating time variability as a key feature, so that the resulting model tends to be static in response to demand fluctuations. Meanwhile, Vlachos and Reddy (2025) Focuses on an overview of machine learning architecture and trends, which methodologically creates a gap with operational implementation and has implications for the difficulty of direct application in decision-making. In addition, Figuera et al. (2024) emphasizing the validation of clustering statistics without linking them to the context of business decisions, so that the evaluation carried out does not guarantee the managerial relevance of cluster results.

Drawing on previous studies, several scientific and practical limitations remain insufficiently addressed in an integrated manner. From a scientific perspective, most research continues to rely on aggregate indicators such as average sales and transaction frequency, without simultaneously incorporating intermittent metrics like Average Demand Interval (ADI) and Coefficient of Variation (CV). Moreover, classification outcomes are generally confined to analytical purposes and are rarely linked to inventory management strategies. From a practical standpoint, PT JJA still applies a make-to-order procurement approach without leveraging historical data as a basis for product segmentation, resulting in demand patterns not being fully utilized to support more precise and data-driven decision-making.

This study uses an unsupervised learning-based data mining approach with the K-Means Clustering algorithm to group products based on similar demand patterns. This approach integrates temporal indicators such as average sales, coefficient of variation (CV), number of periods without sales, Average Demand Interval (ADI), and demand trends, so that it is able to represent demand dynamics more comprehensively. This study is important because it connects clustering techniques in data mining with inventory management based on demand characteristics, which so far generally still uses simple aggregate indicators and has not been able to capture simultaneous intermittent and dynamic demand patterns.

The simultaneous use of time-based demand indicators, average sales, fluctuation rates, sales consistency, number of months without sales, and demand trends, as well as the integration of grouping results into procurement recommendations differentiates this approach from conventional segmentation. This method goes beyond aggregate indicators by including temporal dimensions as an explicit representation of demand patterns that were not previously combined in a single grouping process, resulting in a more representative product classification to support decision-making on amulti-SKU system.

This study aims to apply the K-Means Clustering algorithm in product segmentation based on temporal demand patterns on PT JJA's sales data, as well as identify cluster characteristics and formulate procurement strategies based on segmentation results. The contribution of this study is to provide a data mining approach that can be used as part of a decision support system to support more targeted inventory management.

METHOD

This study uses an exploratory unsupervised learning design with a data mining approach using the K-Means algorithm for product segmentation based on temporal demand patterns at PT JJA. K-Means was chosen for efficiency on large data, although it has limitations in handling outliers and determining the optimal number of clusters early in analysis. Methods such as DBSCAN, hierarchical clustering, and GMM were excluded due to uneven density data, high computational complexity, and normal distribution assumptions.

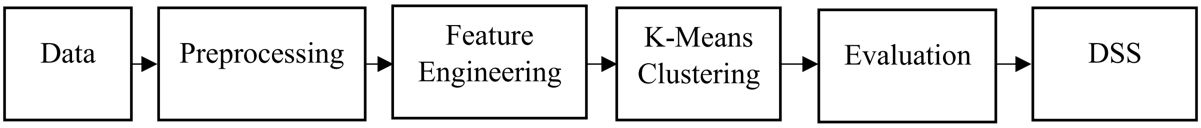

Figure 3. Research methodology pipeline

Figure 3 presents the systematic research flow from pre-processing, feature engineering, grouping of K-Means, cluster evaluation, to the utilization of results in procurement DSS. The object of the study is PT JJA with 11,988 transactions for the 2020–2025 period, including the COVID-19 period. The data shows the distribution of long tail, a small percentage of the product is sold very often, while the majority is rarely sold (see Table 1). This imbalance is maintained as a natural character of a multi-SKU system. Data was collected through observation, interviews, and documentation, and then cleaned, standardized, and normalized using Z-score due to K-Means' sensitivity to the Euclidean scale. Outliers are maintained as a representation of intermittent surge in demand. There are no lost values and months without transactions are recorded as zero. The data is then converted into a monthly sales matrix per product to support the analysis of temporal demand patterns in inventory management.

Table 1. Monthly sales data per product

Product Code	Jan-2020	Feb-2020	Mar-2020	…	Oct-2025	Nov-2025	Dec-2025
AA-1510	0	0	1	…	0	0	0
AA-1520	0	0	0	…	0	0	0
AA-1530	0	0	0	…	0	0	0
AA-1540	0	0	0	…	0	0	0
AA-1550	5	0	0	…	0	0	0

The derived attributes obtained from processing the data in Table 1 into statistical measures such as average demand, coefficient of variation (CV), number of active months, proportion of zero-sales months, Average Demand Interval (ADI), and trend are presented in Table 2, capturing the underlying demand characteristics and serving as key inputs for the clustering analysis.

Table 2. Product attribute formation results

Product Code	Total Qty	Mean Monthly	CV	Active Months	Zero Month Ratio	ADI	Trend
AA-1510	7	0.097	3.49	6	0.92	12	0.0004
AA-1520	7	0.097	3.04	7	0.90	10.29	0.0021
AA-1530	9	0.125	2.96	8	0.89	9.00	0.0007
…	…	…	…	…	…	…	…

Evaluation of the number of clusters using the Elbow and Silhouette Score method. Elbow assesses the SSE's decline against k-variation to find a slowdown point, while Silhouette measures the quality of cluster separation in the range of -1 to 1. The determination of k is optimal based on the combination of both. Data processing is done in Python (Google Colab) with Excel support. K-Means runs on k2–10, k-means++ initialization, max_iter 300, and random_state. The result is in the form of product grouping based on temporal demand patterns as the basis for procurement strategy recommendations.

RESULTS AND DISCUSSION

Results

The dataset consists of 11,988 transactions that have been processed into 261 products with a representation of monthly sales over 72 periods. Most products have a low sales frequency, while a small percentage of products have a higher sales frequency. Feature engineering produces zero_month_ratio values with an average of more than 0.80 on most products. The ADI value is in the range of about 3 to more than 12 months. The value of the CV is in the range of ±0.8 to more than 3.5.

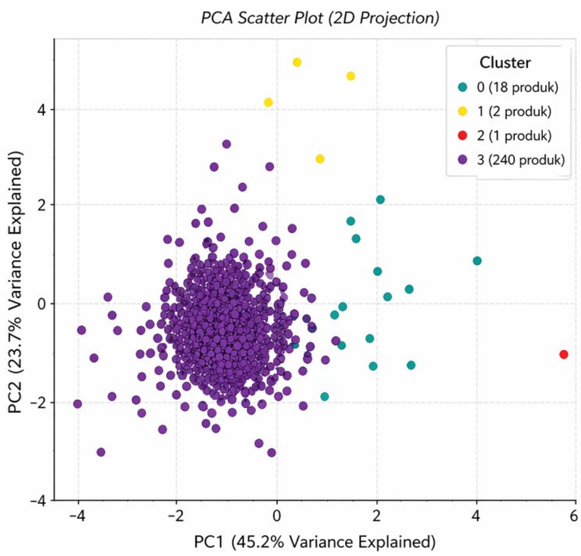

Figure 1. Cluster separation visualization (pca projection)

Determination of the number of clusters resulted in k = 4 as the configuration used. The Sum of Squared Error (SSE) value decreased to k = 4 and slowed down thereafter. The highest

Silhouette Score value was obtained at k = 4 which was about 0.62, compared to k = 3 (~0.54) and k = 5 (~0.58). The cluster distribution consisted of 240 products in Cluster 3, 18 products in Cluster 0, 2 products in Cluster 1, and 1 product in Cluster 2.

Figure 1 contains a visualization of cluster separation using two-dimensional PCA projection. The projection results in a clear cluster separation between the dominant Cluster 3 and the cluster with a small number of members. The points in Clusters 0, 1, and 2 are in a more scattered position and are far from the center of Cluster 3 in the projection plane of the two main components. The difference in position between clusters represents the difference in demand characteristics in each cluster during the data observation period.

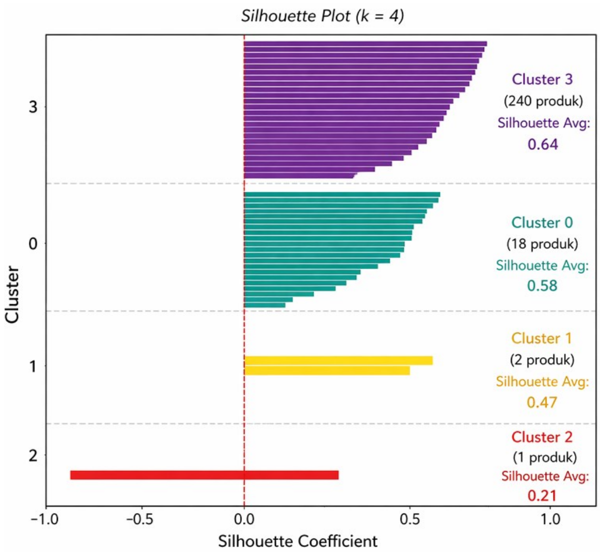

Figure 2. Silhouette plot

Figure 2 contains a silhouette plot showing most of the products in Cluster 3 with positive and relatively high silhouette values, reflecting the good grouping consistency of most of the cluster members during the segmentation process. Meanwhile, the products in the small cluster still have a positive silhouette value, so even though the number of members is small, the separation formed remains structurally valid, consistent, and clearly separate based on the proximity of the demand feature characteristics between the products.

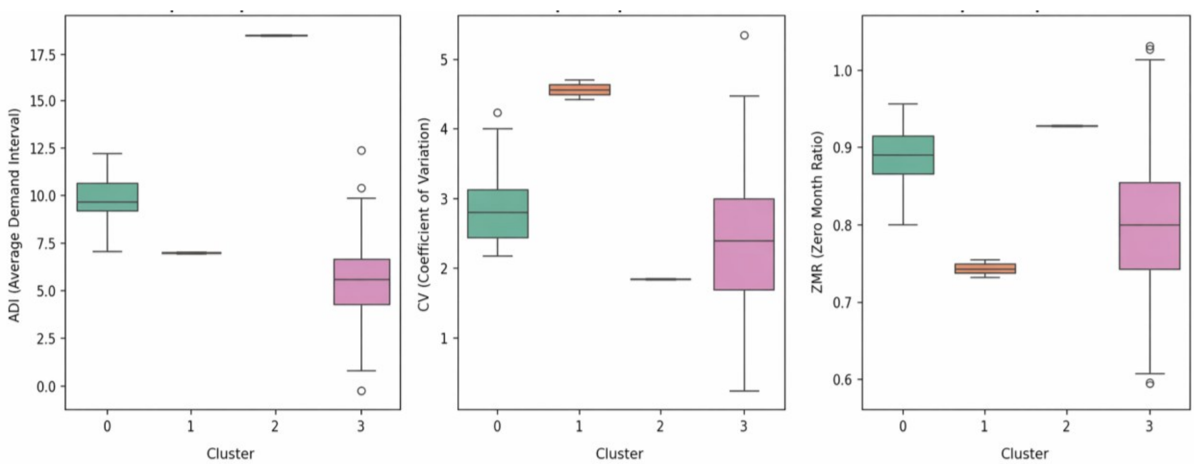

Figure 3. Distribution of adi, cv, and zmr values in each cluster

Figure 3 contains the distribution of ADI, CV, and ZMR values in each K-Means result cluster. There are differences in characteristics between clusters. Cluster 2 has the highest ADI and ZMR values, with very rare demand patterns, long intervals between transactions, and many months without sales (very rare demand). Cluster 1 has the highest CV value, with extreme and unstable demand fluctuations. Meanwhile, Cluster 3 with the most product members has a distribution of ADI, CV, and ZMR at the intermediate level, which represents the dominant moderate intermittent demand pattern in the multi-SKU system. This visualization confirms that each cluster has a structurally different demand pattern and cannot be managed with a uniform procurement approach.

Cluster 3 consists of 240 products. Clusters 0, 1, and 2 consist of 18, 2, and 1 products, respectively. Products in cluster 3 have ADI and CV values in the medium to high range. Meanwhile, products in clusters with smaller members have higher ADI values or larger CV values (CV > 3), with sparse, fluctuating, unpredictable, and unstable demand patterns during the observation period. These findings confirm that the demand structure in a multi-SKU system is not homogeneous, but rather dominated by products with intermediate patterns as well as a small number of products with extreme behavior, which cannot be managed with a uniform procurement approach. Therefore, adaptive and segmentation-based procurement strategies are needed to accommodate differences in demand characteristics between products more effectively and efficiently.

The distribution of the number of cluster members is patterned by a long-tail distribution, most of the products are concentrated in a single cluster (Cluster 3). A small number of products are in clusters with extreme characteristics. This condition is commonly found in multi-SKU inventory systems. The centroids-based nature of K-Means leads to the tendency to form one large cluster that represents a general pattern. Products with extreme behavior separate into small clusters. This is not a weakness, but rather the ability of K-Means to isolate demand patterns that deviate from the majority.

Table 3. Distribution of the number of products in each cluster

Cluster	**Count**
0	18
1	2
2	1
3	240

Table 3 presents the distribution of the number of products in each cluster. Cluster 3 consists of 240 products, while Cluster 0, Cluster 1, and Cluster 2 consist of 18, 2, and 1 products, respectively, with the predominance of products with the same characteristics and the presence of a small number of products with very different demand patterns, in the range of frequency, variation, interval, and consistency of sales between time periods.

The stability test was carried out by rerunning the K-Means algorithm using several different random seed values. The results obtained were consistent in the grouping of products in the same cluster, especially in the dominant Cluster 3. All products in Cluster 3 remained in the same cluster each time the iteration process was rerun. The products in Clusters 0, 1, and 2 also did not move between clusters even though the initial centroid used was different. Based on these findings, the cluster structure formed was proven to be stable, robust, and not dependent on initial initialization. This strengthens the validity of the segmentation results that have been obtained previously.

Table 4 contains the differences in demand pattern characteristics between K-Means product clusters at PT JJA based on the average ADI, CV, ZMR, and trends. Clusters with high ADI and ZMR represent products with long demand intervals and many months without transactions, reflecting very rare demand. Clusters with the highest CV reflect extreme and unpredictable demand fluctuations. Meanwhile, clusters with ADI, CV, and ZMR values at the medium level but with the most product members describe the dominant moderate intermittent demand pattern in multi-SKU systems. The difference in trend values between clusters confirms that there is a variation in demand trends over time, so the results of this segmentation are relevant as the basis for determining procurement strategies and inventory control.

Table 4. Average value of adi, cv, zmr, and trend per k-means result cluster at pt jja

cluster	Avg ADI	Avg CV	Avg ZMR	Avg trend
0	9.87	3.12	0.91	0.004
1	6.21	4.85	0.73	-0.012
2	18.44	2.02	0.96	0.001

Clusters with a small number of members still have a good silhouette value, which reflects a consistent separation between groups. This condition indicates that the cluster structure has a good level of interpretability, where each cluster is formed based on clear differences in demand characteristics, both in terms of frequency, variation, and transaction patterns between observation periods.

Table 5. Examples of product clustering results

Product Code	Item Name	Cluster	Cluster Type	Procurement Strategy
AA-1510	HONEYWELL EDA 52	3	Moderate/ Special	Selective Procurement/ Monitoring
AA-1520	Water Wind Glue Shot Caulking Gun	3	Moderate/ Special	Selective Procurement/ Monitoring
AA-1530	CBA-R07-S07PAR Cable RS232	3	Moderate/ Special	Selective Procurement/ Monitoring
AA-1540	DS3678-SR Rugged Scanner Kit	3	Moderate/ Special	Selective Procurement/ Monitoring
AA-1550	310P1.25 NAC Impact Sockets	3	Moderate/ Special	Selective Procurement/ Monitoring
AA-1560	Makita GA 4030	3	Moderate/ Special	Selective Procurement/ Monitoring
AA-1570	Tube Package APAR Tonata ABC 1 Kg	3	Moderate/ Special	Selective Procurement/ Monitoring
AA-1580	Tube Package APAR Tonata HFC 6 Kg	3	Moderate/ Special	Selective Procurement/ Monitoring
AA-1590	Tube Package APAR Tonata HFC 1 Kg	3	Moderate/ Special	Selective Procurement/ Monitoring

Table 5 presents examples of products grouped by cluster. This table contains information about product codes, item names, cluster labels, cluster types, and procurement strategies. The products shown in table 5 are from Cluster 3. The final result of this study is the collection of product grouping data that can be used as a basis for evaluating demand patterns and formulating inventory procurement strategies in the company, as well as providing an analytical basis to support more accurate, additive, and demand-based decision-making for each product in the context of complex multi-SKU inventory management.

Discussion

This study shows that the formation of highly unbalanced clusters, with the dominance of products in one large cluster and a small number of products in extreme clusters, has important theoretical significance. This structure has to do with the natural character of multi-SKU systems, where most products are on a medium demand pattern that appears relatively rarely but not completely sporadic, while few products are actually highly volatile or highly stable. This kind of distribution is in line with the character of long-tail demand distribution in the product portfolio, so grouping is naturally concentrated in one large cluster with several extreme clusters (Bi et al., 2023). This condition explains the limitations of the uniform procurement approach that is classically assumed in the demand homogeneity-based inventory model. The dominance of Cluster 3 that houses most of the products is not solely a numerical result, but reflects that the majority of items in the distribution system have a moderate intermittent demand character. These products do not have a high frequency of demand, but they are also not completely random, so conceptually form large groups with similar temporal characteristics. This dominance shows that in the classification of demand, the intermediate pattern is the main representation of the portfolio, while the extreme pattern represents only a small percentage of the product.

The high ADI value in some clusters has the conceptual implication that the distance between requests is a more decisive dimension than the volume of demand itself. The frequency of demand emergence becomes a more relevant indicator than the aggregate sales volume, as products with small volumes but long intervals have different behaviors than short-interval products, a concept that is reflected in the ADI–CV approach to the classification of demand patterns and changes in demand behavior in SKUs that have a Long demand interval (Neu et al., 2024). This expands the classic perspective of inventory management which has so far emphasized the magnitude of demand rather than the rhythm of its emergence.

K-Means builds clusters by defining centroids as the center of data mass. This algorithm minimizes intra-cluster spacing through iterative optimization, resulting in mutually exclusive partitions (Kaur et al., 2024). Farahnakian et al. (2023) asserts that the main objective function of K-Means is to minimize within-cluster variance so that separation between clusters occurs naturally through such optimization. In contrast to the commonly used transaction frequency-based grouping or static aggregate value approach, this study expands the representation of data by integrating temporal features such as zero_month_ratio, ADI, coefficient of variation, and demand trends. This integration transforms the data structure from a mere transaction intensity to a dynamic representation of demand behavior, so that the grouping reflects not only the size of demand, but also the patterns of regularity and fluctuations in demand across each product (Mudgal, 2026). Thus, the use of this temporal feature provides a richer perspective on data mining-based product segmentation, particularly in the context of multi-SKU data with non-uniform demand patterns.

Previous study as shown that the use of machine learning and clustering techniques in demand analysis and supply chain management has evolved, but it still has limitations in comprehensively capturing temporal dynamics. In line with Giannopoulos et al. (2023), placing intermittent requests at the level of general model synthesis without specification of operational temporal features, so that methodologically it does not provide guidance for time-based data representation and has implications for segmentation that is less sensitive to temporal variations. Meanwhile, Tarragó et al. (2023) adopt temporal data in homogeneous contexts without addressing the implications of those context's limitations, so that the generalization of the model to heterogeneous multi-SKU systems becomes weak. In contrast to Keskin and Taşkın (2024) propose an artificial intelligence-based inventory classification at a conceptual level without formulating time variability as a key feature, which has implications for classification models that tend to be static to real demand fluctuations. Complete Vlachos and

Reddy (2025), focuses on the integration of analytical models and machine learning architectures without explaining the methodological implications of the gap with operational practices, resulting in limited direct application in decision-making. This sudy is also in line with the results of the study Figuera et al. (2024) emphasizing statistical validation of clustering without identifying methodological weaknesses of the approach in the context of business decisions, so the managerial relevance of cluster results is not guaranteed.

In contrast to static aggregate-based approaches such as total or average sales, this study uses temporal features (zero_month_ratio, ADI, and CV) so that demand is understood as a dynamic process with a structure of regularity, irregularity, and emptiness, in line with the feature-based forecasting literature for intermittent demand (Li et al., 2023). This shift has the theoretical implication that product classification is not enough based on demand volume alone, but it is necessary to consider temporal dimensions to more accurately identify intermittent patterns, especially in probabilistic forecasting that is directly related to inventory decisions (Park & Rogetzer, 2022). Thus, this study expands the classification of classical inventory from an aggregate approach to segmentation based on temporal dynamics.

This study contributes in three principal dimensions. First, it develops a temporal feature–based segmentation framework for multi-SKU systems by integrating zero_month_ratio, ADI, coefficient of variation, and trend to capture intermittent demand dynamics. Second, it reconceptualizes K-Means from a purely numerical clustering method into an analytical instrument for revealing latent demand structures shaped by temporal variability and uncertainty. Third, it links segmentation outcomes to operational decision-making, enabling differentiated inventory strategies such as safety stock determination and order frequency optimization. Collectively, this approach advances a shift from aggregate-based classification toward temporally grounded segmentation, with novelty residing in the transformation of demand representation into dynamic, behavior-oriented structures.

CONCLUSION

This study shows that K-Means Clustering in PT JJA's sales data produces four demand pattern clusters with uneven distribution, where Cluster 3 dominates as many as 240 products, reflecting the long-tail characteristics of the multi-SKU system. These findings confirm that most products fall into the category of low or unstable demand. The main contribution of this study is the use of temporal indicators such as variation coefficient, month ratio without sales, ADI, and trends that enrich segmentation compared to the sales volume-based approach, thus providing a more informative representation of demand patterns for procurement decision-making. Practically, these results support the design of a more adaptive procurement strategy based on the characteristics of each cluster. However, this study is still limited to internal historical data without considering external variables such as macroeconomic conditions. Further study can develop this approach with time series-based models such as LSTM or ensemble learning to improve the accuracy of demand analysis.

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