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Drug Use Pattern Analysis Model Using the K-Means Algorithm as a Basis for Stocktaking Decision Making

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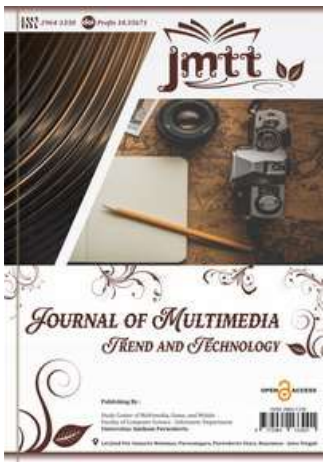

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ABSTRACT

Analysis of drug usage patterns using the K-Means algorithm aims to group drug usage based on its usage level and determine the most optimal number of clusters as a basis for more appropriate and efficient stock management recommendations. This study only focuses on drug usage data for the period of January 1, 2025 to June 30, 2025, with the variables used being the number of drugs used and their frequency of use. The approach used is data mining with the K-Means Clustering method, as well as cluster evaluation using the Elbow Method and Silhouette Coefficient. Using the Elbow method, the appropriate number of clusters is 3. This is indicated by the elbow point at k = 3, where the decrease in the WCSS value begins to decrease significantly. Evaluation of clustering quality using the Silhouette Score and Daevis-Bouldin Index (DBI) shows that the formed cluster structure has good quality. The Silhouette Score value reaches 0.61 and the DBI value is 0.53. This indicates that the data in each cluster is quite homogeneous, and the separation between clusters is quite optimal. The analysis results show that the most optimal number of clusters is three clusters, representing drug categories with high (fast-moving), medium (medium-moving), and low (slow-moving) usage levels. Each cluster has different but consistent usage characteristics. These findings provide a clear picture of the distribution pattern and drug needs at the Purwokerto Utara II Community Health Center, and help identify the possibility of deadstock and stockouts. Thus, it can be concluded that the application of the K-Means algorithm is very effective in supporting drug stock management decision making, so that drug procurement planning can be carried out more accurately, efficiently, and sustainably.

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INTRODUCTION

A Community Health Center is a health service provider that serves as a hub for community health development. Puskesmas are responsible for implementing comprehensive and integrated health efforts. Minister of Health Regulation Number 19 of 2024 concerning the Implementation of Puskesmas explains that Puskesmas are required to provide promotive, preventive, curative, rehabilitative, and palliative health services within their respective jurisdictions [1]. This demonstrates that Puskesmas function not only as direct health service centers but also play a role in maintaining the quality of public health on an ongoing basis, from prevention to disease management [2].

To carry out these duties, Puskesmas require the support of an integrated service system, particularly in the pharmaceutical sector. Pharmaceutical services play a crucial role in ensuring the availability, safety, and appropriate use of medications for the community. In line with Puskesmas' primary focus on prevention and health promotion efforts within their jurisdictions, a sound medication management system is crucial for maintaining the quality of healthcare services [3].

However, research shows that clinical pharmacy services at community health centers (Puskesmas) are not yet optimal, particularly in terms of management, recording, and documentation [2][4]. Limited pharmacist staff, a lack of monitoring and evaluation activities, and an unintegrated pharmaceutical information system result in inefficient pharmaceutical service processes [5]. This situation has the potential to impact drug availability, as inaccurate planning and management data can lead to an imbalance between drug needs and supplies.

A similar situation occurs at the Purwokerto Utara II Community Health Center, where drug management is still carried out periodically every three months using stock cards and defect books. Recording is carried out when stocks begin to run low, so stock control is reactive and relies on staff observation. This approach does not take into account changes in drug usage levels over time. As a result, some types of drugs experience deadstock, while others experience stockouts. This manual recording method also does not optimally utilize historical drug user data, potentially causing delays in anticipating stock shortages or excesses.

These issues highlight the need for a data-driven approach to more accurately analyze drug usage patterns. One relevant approach is data mining, the process of exploring and extracting important information from large, complex data sets. In data mining, clustering is a commonly used technique for grouping data based on similar characteristics [5]. One widely used algorithm is K-Means, which can group data without requiring initial labels and is effective when applied to large amounts of data.

Several previous studies have demonstrated the effectiveness of K-Means in clustering drug data to support stock management in hospitals and pharmacies, although its application at the community health center level is still relatively limited [6]. Several methods used in data mining include classification, regression, variable selection, and clustering. Among these methods, clustering is the most commonly used technique, particularly K-Means, which effectively groups data based on similar characteristics [5][7]. This method falls into the unsupervised learning category and is suitable for analyzing drug usage patterns and identifying groups of drugs with similar usage characteristics [8][9].

The application of K-Means in drug management has been carried out in various studies in grouping drug data in hospitals using the Elbow and Gap Statistics methods, producing slow-moving and fast-moving drug clusters to support procurement optimization [10][11]. The application of K-Means to drug sales data in pharmacies with an evaluation of the Silhouette Coefficient (0.520) indicates quite good cluster quality [12]. The KDD approach successfully separates drugs with high and low usage to support hospital stock policies [13]. On an international scale, using K-Means to group health insurance prescription claims into three risk levels [14].

Although various studies have demonstrated the efficacy of K-Means, its application to medication management in community health centers remains limited. Without a structured analysis of medication usage patterns, community health centers are at risk of inventory imbalances, either in the form of stockouts of highly used medications or deadstock of infrequently used medications [16]. The impact of this condition not only impacts pharmaceutical logistics efficiency but also has the potential to reduce the quality of healthcare services [3][12][17].

The K-Means Clustering method is considered suitable for addressing this problem because it can group medications based on similarity in level and frequency of use. The clustering results can identify medication categories with high, medium, and low movement rates. This information serves as the basis

for developing different procurement and stock control strategies for each category, resulting in more targeted, efficient, and data-driven medication management [18].

Therefore, this study was conducted to identify medication usage patterns at the Purwokerto Utara II Community Health Center using the K-Means Clustering method and analyze the impact of these clustering results on medication management governance, thereby minimizing the risk of stockouts and deadstock.

METHOD

This study was conducted using drug usage data from the Purwokerto Utara II Community Health Center, with 6,503 patients. The study is planned to last five months, from January 2025 to June 2025. This research concept is based on the goal of identifying and analyzing drug usage patterns to inform drug stock management policies. It uses a data mining approach, specifically the K-Means clustering method. K-Means is used to group drug usage data based on usage levels.

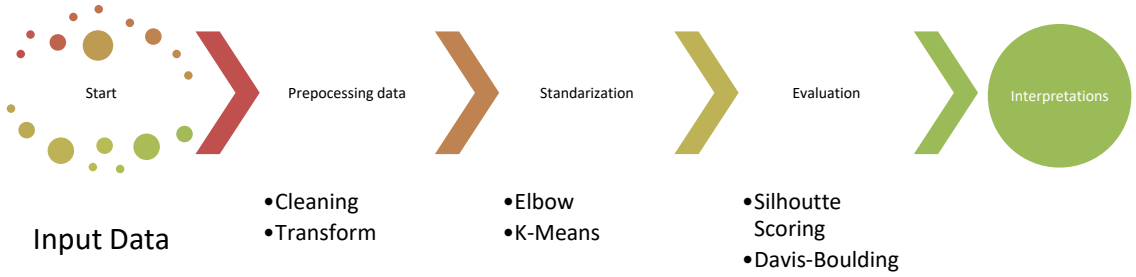


Figure 1. Research Concept

A. Pre-Processing

After the data has been entered, the next step is to prepare it for use in further analysis. The data that has been understood needs further processing to produce a correct and accurate model. This data processing process is crucial because it helps ensure the data used does not contain any issues that could interfere with the analysis results.

1. The primary focus of this data cleaning stage is adjusting the date format, as the obtained drug usage data contains variations in date formatting. Therefore, the date format is converted to a uniform format to ensure consistent data processing [19]. The purpose of this stage is to ensure there are no errors in grouping data by time and to ensure data consistency before entering the transformation stage.
2. The data transformation stage was carried out to convert the drug usage data into a format suitable for clustering analysis. At this stage, drug usage data was collected by calculating the total number of uses and frequency of use for each drug type from January to June 2025. This transformation process converted daily drug usage data into aggregated data per drug type, resulting in a numerical dataset ready for use as input in the K-Means algorithm.

B. Standarization.

Data standardization was performed to ensure all variables had the same scale and balanced their contribution to the analysis process. Attributes such as Number of Drugs and Frequency were standardized using the Standard-Scaler method [20]. The goal was to eliminate scale differences between attributes that could bias the attribute with the highest value. By standardizing, the influence of each attribute becomes more proportional, and the resulting clustering results are more accurate and representative.

1. The Elbow method is used to determine the optimal number of clusters in the K-Means algorithm. This method works by calculating the Within-Cluster Sum of Squares (WCSS) value for various numbers of clusters (k). The WCSS value indicates the level of compactness of the data within a cluster, where the smaller the WCSS value, the better the quality of the clusters formed. This process is carried out by trying several values of k in stages, then the results are displayed in

graphical form. The point where the decrease in the WCSS value begins to slow significantly will form an obtuse-angled section (Elbow) which indicates the appropriate number of clusters.

2. This stage is the core process for applying the K-Means clustering algorithm to discover drug usage patterns. Before clustering, the Elbow method was used to determine the most appropriate number of clusters. The evaluation results showed that the best number of clusters was three clusters (k=3). Next, the K-Means algorithm was run to group drug data based on similarities in quantity and frequency of use during the period from January to June 2025. Thus, three drug groups were formed: high-use (fast-moving), medium-use (medium-moving), and low-use (slow-moving).

C. Evaluation.

Cluster quality evaluation is performed to assess the effectiveness of the clustering results obtained from the K-Means algorithm. In this study, the evaluation was conducted using two methods: the Silhouette Score and the Daevis-Bouldin Index (DBI). The Silhouette Score measures how well data fits together, ranging from -1 to 1. The closer it is to 1, the better the cluster quality. On the other hand, the DBI measures the level of similarity between clusters, where a smaller value indicates more optimal separation between clusters.

D. Interpretation.

The cluster results were interpreted by analyzing the characteristics of each cluster based on the attributes of the number of drugs and their frequency of use. Each cluster was analyzed to identify similar drug usage patterns, thus identifying drug groups with high, medium, or low usage rates. This interpretation provides more comprehensive information regarding drug distribution patterns and needs and can be used as a basis for decision-making related to drug inventory planning and management.

RESULT

A. Model Performance

This study used drug usage data collected from the Puwokerto Utara II Community Health Center from January 1, 2025, to June 30, 2025, totaling 6,503 records. The dataset consisted of several attributes: date, drug name, unit of administration, and quantity.

Table 1. Drug Use Pattern Dataset.

No.	Dates	Drug Names	Pcs	QTY
1.	Wed, 02 January 2025	2-4 CREAM	POT	3.0
2.	Wed, 02 January 2025	ACYCLOVIR SK	TUB	1.0
3.	Wed, 02 January 2025	ACYCLOVIR 400MG TABLET	TAB	12.0
4.	Wed, 02 January 2025	ALLUPURINOL 100MG TABLET	TAB	10.0
5.	Wed, 02 January 2025	AMBROXOL 30MG TABLET	TAB	48.0
…	…	…	…	…
6.503	Mon, 30 June 2025	ZINC 20 MG TABLET	TAB	10.0

Before the clustering process is carried out, the data goes through several pre-processing stages which aim to improve the quality of the data so that it is more ready for use in modeling.

B. Pre-Processing

In this study, the pre-processing stages included data cleaning, data transformation, and data standardization to ensure the data used was of good quality and could produce optimal clustering.

1. Data *Cleaning*.

The first step is to standardize the date format, as described in Algorithm 1 (DateConversion). This process converts dates written in Indonesian into a standard datetime format, simplifying computational processing. The result of this step is consistent date attributes ready for use in further analysis.

Table 2. Data Cleaning Results Date Format Matching

Dates	Drugs Name	PCS	QTY
2025-01-02	2-4 SALEP	POT	3.0
2025-01-02	ACYCLOVIR SK	TUB	1.0
2025-01-02	ACYCLOVIR 400MG TABLET	TAB	12.0
2025-01-02	ALLOPURINOL 100 MG TABLET	TAB	10.0
2025-01-02	AMBROXOL 30 MG TABLET	TAB	48.0

Table 2 displays the results of the date format conversion process. All values in the date attributes that previously had different formats have been successfully converted to the standard YYYY-MM-DD format, ready for use in the next analysis stage.

2. Data Transform.

After the data was cleaned, a transformation process was performed using Algorithm 2 (Drug Data Recapitulation). In this stage, all data was grouped by drug name to obtain two key research attributes:

a. Total number of drug uses

b. Frequency of drug use

These two attributes were used as input variables in the clustering process. This transformation transformed the daily transaction data into a summary of the usage patterns of each drug type during the study period.

```
Algoritma 2 RekapitulasiDataObat
procedure REKAP_DATA_OBAT (DataFrame df)

    Initialize df_summary ← empty DataFrame
    Group df by "Nama Obat" into G

    for each group g in G do
        total ← Sum (g["Jumlah Obat"]
        freq ← Count (g["Tanggal"]
        Append (g["Nama Obat"], total, freq) to df_summary
     end for

     Return df_summary

end procedure
```

Table 3. Data Transformation Results

Drugs Name	QTY	Frequency
2-4 SALEP	62.75	55
ACETYLCYSTEINE 200 MG KAPSUL	1395.00	56
ACYCLOVIR 400MG TABLET	1122.00	67
ACYCLOVIR SK	121.00	70
ALBENDAZOLE 400 MG TABLET	11.00	6

Table 3 shows the results of the drug use data transformation process after merging based on drug name. Each row in the table represents a single drug type and has two main attributes: the total number of drugs uses and the frequency of use during the study period.

C. Data Standardization

Because the drug quantity and frequency attributes have different scales, a standardization process was performed using Algorithm 3 (Data Standardization). The StandardScaler method was used to normalize both attributes so that they have a mean of zero and a standard deviation of one. This standardization aims to prevent the dominance of one attribute in the clustering process and to improve the stability of the modeling results.

Table 4. Standardization Results in the Number of Drugs and Frequency Columns

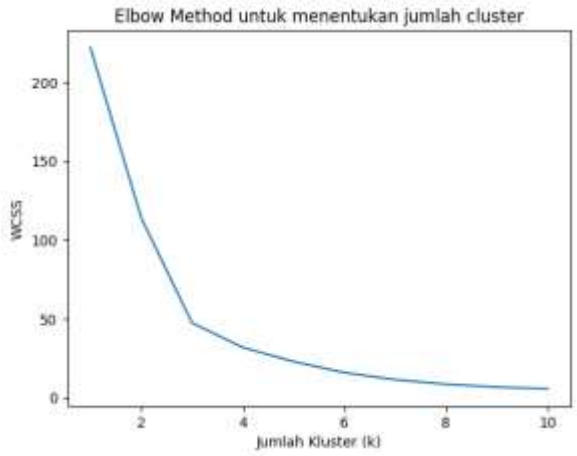
Drugs Name	QTY (Scaled)	Frekuency (Scaled)
2-4 SALEP	-0.410218	-0.073957
ACETYLCYSTEINE 200 MG KAPSUL	-0.173744	-0.053331
ACYCLOVIR 400MG TABLET	-0.222202	0.173559
ACYCLOVIR SK	-0.399878	0.235438
ALBENDAZOLE 400 MG TABLET	-0.419403	-1.084648

Table 4 shows the results of the standardization process for the Number of Drugs and Frequency attributes using the Standard-Scaler method. This process converts both attributes to the same scale with a mean value close to zero and a standard deviation of one. Standardization is necessary to prevent attributes with higher values from dominating the distance calculation, which could lead to unbalanced clusters. Therefore, the standardized data is used as the primary input in determining the number of clusters and in subsequent clustering processes.

D. Elbows Method

The optimal number of clusters is determined using the Elbow Method, as described in Algorithm 4 (Elbow Method). The Within-Cluster Sum of Squares (WCSS) value is calculated from the number of clusters from 1 to 10.

Table 5. Results of the Elbow Method



Cluster (k)	WCSS
k=1	222.0
k=2	114.0454351791933
k=3	47.466705554606115
k=4	31.824599605551878
k=5	22.87185517567284
k=6	15.853292178275405
k=7	11.401817115052044
k=8	8.478803519738022
k=9	6.694591524649616
k=10	5.583741068100758

Table 5 displays the WCSS values for various numbers of clusters, from k=1 to k=10. WCSS describes the level of data variation within each cluster, where the smaller the WCSS value, the more homogeneous the data within the cluster. Table 6 shows that the WCSS value experiences a significant decrease from k=1 to k=3, namely from 222.0 to 47.47. After k=3, the decrease in the WCSS value begins to slow down and no longer shows a sharp change. This pattern indicates that increasing the number of clusters after k=3 does not provide a significant increase in cluster quality.

The decreasing pattern is more clearly seen in Table 5 using the Elbow method. In the graph, the X-axis represents the number of clusters (k) from 1 to 10, while the Y-axis shows the WCSS value. The

elbow point is clearly visible at k = 3, which indicates a change in the rate of decrease in the WCSS value from steep to gentle. Based on numerical and visual evaluations, the optimal number of clusters to represent the structure of the drug use data in this study is three clusters.

E. K-Means Model

Based on the results of the Elbow method, clustering was performed using the K-Means algorithm with three clusters, as per Algorithm 5 (Kmeans Clustering). This model was trained using standardized data and resulted in a separation of drug data into three groups based on the similarity of their usage patterns.

Table 6. Centroid Value Results Per Cluster

Cluster	QTY Scaled	Frekuency Scaled
1	4.307779	1.833978
2	0.136685	0.901758
3	-0.385551	-0.800275

Table 6 shows the centroid values for each cluster generated by the K-Means algorithm, based on two attributes that have been converted to a standard scale: Number of Drugs (Scaled) and Frequency (Scaled). These centroid values describe the average characteristics of each cluster. Cluster 1 represents the highest centroid value for both attributes, Cluster 2 has a centroid value in the middle, and Cluster 3 has the lowest centroid value.

Table 7. Cluster Label Adjustment Results

Drugs Name	QTY	Frekuency	QTY Scaled	Frekuency Scaled	Cluster
2-4 SALEP	62.75	55	-0.410218	-0.073957	3
ACETYLCYSTEINE 200 MG KAPSUL	1395.00	56	-0.173744	-0.053331	3
ACYCLOVIR 400MG TABLET	1122.00	67	-0.222202	0.173559	2
ACYCLOVIR SK	121.00	70	-0.399878	0.235438	2
ALBENDAZOLE 400 MG TABLET	11.00	6	-0.419403	-1.084648	3

Table 7 shows the final clustering results after adjusting the cluster labels based on the rearrangement process. Label adjustments were made by considering the order of the average number of drugs in each cluster, with the cluster with the highest average value being labeled cluster 1, followed by cluster 2, and finally cluster 3. The goal of this process is to make the clustering results easier to understand.

F. Evaluations

The quality of the clustering results is evaluated by two metrics, namely the Silhouette Score and the Daevis-Bouldin Index, as found in Algorithm 7 and Algorithm 8. From the test results, the Silhouette Score value is 0.61 and the DBI is 0.53. This value indicates that the cluster structure formed has a fairly good separation, with high internal cluster homogeneity and a low level of overlap between clusters.

1. Silhouette Score

   To evaluate the quality of the clustering results produced by the K-Means algorithm, the Silhouette Score method is used.

```
Algoritma 7 EvaluasiSilhouetteScore
procedure HITUNG_SILHOUETTE_SCORE(X_scaled, df_summary)
    labels ← df_summary["Cluster"]
    score ← SilhouetteScore(X_scaled, labels)
    Return score
end procedure
```

2. Davies–Bouldin Index
   In addition to using the Silhouette Score, the quality of the cluster results is also assessed using the Davies–Bouldin Index (DBI). This is to assess the homogeneity between clusters and whether they are well separated.

Algoritma 8 *EvaluasiDaviesBouldin*
procedure *HITUNG_DAVIES_BOULDIN(X_scaled, df_summary)*
    labels ← df_summary["Cluster"]
    DBI ← DaviesBouldinIndex(X_scaled, labels)
    Return *DBI*
end procedure

G. Interpretation Result

The final step is to interpret the clustering results using Algorithm 9 (Cluster Results Interpretation). Each cluster group is analyzed based on the type of drug and its frequency of use.

Table 8. Results of Clustering

Cluster	Drugs Name	QTY	Frekuency
1	AMOXICILLIN 500MG TABLET	24351	148
1	DEXAMETHASONE 0,5 MG TABLET	23927	148
1	PARACETAMOL 500 MG TABLET	43227	148
2	CETIRIZINE 10 MG TABLET	9211	145
2	ASAM MEFENAMAT 500 MG TABLET	8506	143
2	VITAMIN B1 50 MG (THIAMIN) TABLET	10251	143
3	ALLOPURINOL 100 MG TABLET	815	63
3	CHLORAMPHENICOL 1% SALEP MATA	70	57
3	VITAMIN K 10 MG (PHYTOMENADION) TABLET	591	57

Table 8 displays the final results of drug grouping based on usage patterns, analyzed using the K-means algorithm. Each group or cluster represents a group of drugs with distinct usage patterns, defined by the quantity and frequency of use.

The first cluster represents the group of drugs with the highest usage rates (fast-moving). Drugs in this cluster, such as Paracetamol 500 mg, Amoxicillin 500 mg, and Dexamethasone 0.5 mg, have a high volume and frequency of use, demonstrating their importance in daily healthcare services.

The second cluster represents the group of drugs with a medium usage rate (medium-moving). Drugs such as Cetirizine, Mefenamic Acid, and Vitamin B1 show fairly stable usage patterns, not particularly high but still routinely used in healthcare services.

The third cluster reflects the group of drugs with a low usage rate (slow-moving). Drugs such as Allopurinol, Chloramphenicol eye ointment, and Vitamin K have a relatively low volume and frequency of use, potentially leading to stock accumulation if not managed properly.

These results provide useful information to support decision-making in more efficient and effective drug procurement.

CONCLUTIONS

Using the Elbow method, the appropriate number of clusters was 3. This is indicated by the elbow point at k=3, where the decline in WCSS scores begins to decrease significantly. Evaluation of clustering quality using the Silhouette Score and Davis-Bouldin Index (DBI) indicated that the resulting cluster structure was of good quality. The Silhouette Score reached 0.61 and the DBI was 0.53. This indicates that the data within each cluster is quite homogeneous, and the separation between clusters is quite optimal. The clustering results indicate that drug use patterns are divided into three main groups: high-use (fast-moving), medium-use (medium-moving), and low-use (slow-moving). The high-use cluster is dominated by essential drugs frequently used in daily care, such as Paracetamol 500 mg, Amoxicillin

500 mg, and Dexamethasone 0.5 mg, indicating that these medications are primary needs of patients. The moderate-use cluster reflects a group of medications that are used routinely, but not as frequently as the first cluster, such as Cetirizine, Mefenamic Acid, and Vitamin B1.

The low-use cluster is dominated by medications with specific needs and limited frequency of use, such as Allopurinol, Chloramphenicol eye ointment, and Vitamin K. If not managed properly, these medications have the potential to cause stock accumulation. This pattern indicates that medication management at the Purwokerto Utara II Community Health Center requires a different approach for each medication group to prevent deadstock and stockouts.

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