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Cluster Analysis of Food Social Assistance in DKI Jakarta: K-Means Approach to Identify Expenditure Patterns and Beneficiaries

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Abstract: This study aims to evaluate the effectiveness of the K-Means algorithm in grouping social assistance recipients in DKI Jakarta based on various demographic and economic factors, such as income, number of family members, and living conditions. The main objective of this study is to optimize resource allocation in social assistance programs by identifying different recipient clusters, so that aid distribution becomes more targeted. In this study, the K-Means algorithm was used with an optimal number of clusters of 3, and produced an accuracy rate of 85%, indicating that this algorithm is effective in grouping large-scale and complex data. However, there are challenges related to the sensitivity of K-Means to outliers and data imbalances that affect the results of the analysis. The results also show that areas such as Central Jakarta and South Jakarta receive more social assistance compared to other areas such as North Jakarta and East Jakarta, reflecting differences in needs in various regions. These findings emphasize the importance of selecting the right variables, such as access to health facilities and economic conditions, in producing more accurate groupings. Overall, this study provides valuable insights into efforts to optimize the distribution of social assistance in DKI Jakarta and recommends further research to address the limitations that exist in the use of the K-Means algorithm, especially in the context of data that is imbalanced or has large variations.
Keywords: K-Means Algorithm, social assistance, classification, DKI Jakarta, cluster analysis.

INTRODUCTION

Food social assistance is one of the important forms of government intervention to improve people's welfare, especially for underprivileged groups (Tu et al., 2020). In DKI Jakarta, as the capital and economic center of Indonesia, the food social assistance program plays a very significant role in overcoming poverty and social inequality (DKI, 2024). However, the effectiveness of this social assistance is often hampered by the difference between the plan and the realization, both in the number of beneficiary families (KPM) and in the budget used. The following data shows the plan and realization of the number of KPM and the budget for food social assistance in various regions in DKI Jakarta

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Table 1. Planned and Realized Number of DKI Jakarta Social Assistance Beneficiary Families

Regency/City	Planned Number of KPM	Realized Number of KPM	Planned Budget (Rp)	Realized Budget (Rp)
Kepulauan Seribu	9022	8876	Rp3.650.400.000	Rp3.591.600.000
Kota Jakarta Selatan	213231	201048	Rp87.085.600.000	Rp82.046.400.000
Kota Jakarta Timur	245854	236085	Rp100.253.800.000	Rp96.061.400.000
Kota Jakarta Pusat	194612	187283	Rp79.393.000.000	Rp76.370.800.000
Kota Jakarta Barat	310714	291283	Rp128.073.600.000	Rp120.157.200.000
Kota Jakarta Utara	241342	225884	Rp99.030.600.000	Rp92.649.400.000
DKI Jakarta	1214775	1150459	Rp497.487.000.000	Rp470.876.800.000

In Table 1. The data above shows a difference between the plan and the realization in the number of KPM and the budget in each region. For example, in the Seribu Islands, there is a difference between the plan and the

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realization of the number of KPM of 146 and a budget difference of Rp58,800,000. Likewise, in South Jakarta City, there is a difference between the plan and the realization of the number of KPM of 12,183 and a budget difference of Rp5,039,200,000. The effectiveness of social assistance is often hampered by a lack of understanding of spending patterns and characteristics of beneficiaries (Rayanti dkk, 2021).With the increasing number of beneficiaries and the diversity in their characteristics, it is important to conduct in-depth analysis to understand the distribution and receipt of assistance. This analytical approach not only helps in designing more effective policies but also in identifying spending patterns that may not be detected through conventional analysis(Saraswati, 2020). This study aims to identify spending patterns for food social assistance in DKI Jakarta and group beneficiaries using the K-Means algorithm to find clusters that show similar characteristics and spending patterns. Through this study, it is hoped that it can provide useful insights to improve the effectiveness and efficiency of the distribution of food social assistance, so that assistance can be more targeted and have a greater impact on the community..

LITERATURE REVIEW

This literature review aims to review and analyze various previous studies that are relevant to the use of the K-Means algorithm in cluster analysis, especially in the context of social assistance. This section will also identify gaps in previous studies that can be used as a basis for this study.

The K-Means algorithm has become one of the most popular methods in cluster analysis, mainly due to its simple yet effective ability to group data into homogeneous clusters. that K-Means is very suitable for large and complex data analysis, because this algorithm can quickly process data and find hidden patterns. However, this study also highlights some of the disadvantages of K-Means, such as its dependence on choosing the right number of clusters and sensitivity to outliers(K. Wu et al., 2019).

Research conducted by Chen and Lin (2020) also shows how K-Means can be used to cluster beneficiaries in social assistance programs. The study found that by clustering beneficiaries based on demographic and economic characteristics, the government can design more targeted policies. However, they also note that the lack of quality data can affect the results of the cluster analysis(Li & Dkk, 2020).

Several studies have applied the K-Means algorithm to analyze the distribution of social assistance. For example, a study in Indonesia used K-Means to group aid recipients based on factors such as income, family size, and living conditions. The results (Rayanti dkk, 2021), showed that they were able to identify groups of recipients that needed more attention in terms of resource allocation. However, this study also showed limitations in using K-Means when the data is unbalanced or there is large variation between clusters.

Meanwhile, Wahyudi and Saraswati (2022) highlighted the importance of selecting the right variables in cluster analysis. They used K-Means to analyze food social assistance data in several provinces in Indonesia, and found that the resulting clustering was highly dependent on the variables selected. They recommended using variables that reflect key aspects of beneficiaries, such as economic conditions and access to health facilities(Saraswati, 2020).

Although there have been many studies that apply K-Means in social assistance analysis, there are several gaps that need to be considered. First, most studies focus more on the technical aspects of the algorithm and pay less attention to the implementation of policies resulting from the analysis(Huda, 2019). In addition, many studies use limited or less representative data, so the results may not be generalizable to a wider population. In addition, some studies tend to ignore the impact of non-economic variables, such as social and cultural factors, in the grouping of beneficiaries(Wisadirana & Dkk, 2021).

This study aims to fill the gaps in the literature by using more comprehensive data and considering various relevant variables, both economic and non-economic, in cluster analysis. In addition, this study will also link the results of the cluster analysis with policy recommendations that can improve the effectiveness of food social assistance distribution in DKI Jakarta.

METHOD

This section explains the method used in this study to analyze and group food social assistance data in DKI Jakarta using the K-Means algorithm. This method is designed to provide the latest contribution in solving the problem of inefficient distribution of social assistance by identifying previously unrevealed patterns of spending and beneficiaries. The data used in this study were obtained from the Central Statistics Agency (BPS) of DKI Jakarta and the DKI Jakarta Social Service. This data includes the planned and realized number of beneficiary families (KPM), as well as the food social assistance budget from various districts/cities in DKI Jakarta. This data covers the period from [Year] to [Year], thus providing a comprehensive picture of the distribution of social assistance in this region(DKI, 2024).

The data obtained will go through a pre-processing stage to ensure the quality and suitability of the data for the analysis to be carried out. Pre-processing steps include:

1. Data Cleaning: Deleting or correcting missing data, inconsistent data, or duplicate data (Chen & Lin, 2020)
2. Data Normalization: Converting data to the same scale to prevent bias in the clustering process (Y. Wu et al., 2019).

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3. Feature Selection: Selecting the most relevant variables for analysis, such as the number of KPM, allocated budget, and budget realization (Rayanti dkk, 2021).

The K-Means algorithm will be used to group data based on spending patterns and beneficiaries. The clustering process will be carried out in the following stages:

1. Determining the Number of Clusters (K): Using the elbow method to determine the optimal number of clusters to be used(Saraswati, 2020).
2. Cluster Initialization: Randomizing the initial center points for the clusters.
3. Algorithm Iteration: Allocating each data point to the nearest cluster based on the Euclidean distance and recalculating the cluster center points until convergence(Y. Wu et al., 2019).
4. Cluster Evaluation: Using Silhouette Score and Inertia to evaluate the quality of the resulting clusters(Chen & Lin, 2020).

To facilitate the interpretation of clustering results, data visualization will be done using diagrams and graphs. Some of the visualizations used include:

1. Scatter Plot: Displays the distribution of KPM and budget based on clusters..
2. Cluster Centroid Plot: Menunjukkan titik pusat dari setiap klaster untuk mengidentifikasi karakteristik umum dalam masing-masing klaster (Satriatama & Dkk, 2023).
3. Elbow Method Plot: Used to determine the optimal number of clusters by displaying cluster variance against the number of clusters (Rayanti dkk, 2021).

K-Means is a clustering algorithm used to group data into a predetermined number of clusters, with the main goal of minimizing variance within each cluster, measured by the Euclidean distance between data points and the cluster centers (centroids).

K-Means Steps (Ernawati et al., 2023):

1. Initialization: Randomly select kk initial centroids from the dataset.
2. Clustering: Assign each data point to the nearest cluster based on Euclidean distance from the centroids.
3. Recalculation: Recalculate the centroids as the average of all data points included in each cluster.
4. Iteration: Repeat steps 2 and 3 until the centroids no longer change or the changes are very minimal, indicating convergence.Rumus-Rumus K-Means

1. Euclidean Distance: To calculate the distance between a data point xix_ixi and a centroid cjc_jcj, the formula used is:

$$d(xi,cj) = \sqrt{\sum_{i=1}^{n}(xi,l - cj.l)^2} \qquad (1)$$

where xix_ixi is the data vector for the iii-th data point, cjc_jcj is the centroid vector for the jjj-th centroid, and nnn is the number of features.

2. Centroid Update Formula: After data points are assigned to clusters, the new centroid for cluster jjj is calculated as:

$$c_j^{new} = \frac{1}{|C_j|} \sum_{xi \in c_j} xi \qquad (2)$$

where ∣Cj∣|C_j|∣Cj∣ is the amount of data in the jth cluster, and CjC_jCj is the data set in the jth cluster.

3. Objective Function (Total Inertia): The objective function to be minimized in K-Means is the total distance within the cluster (inertia):

$$J= \sum_{j=1}^{k} \sum_{xi \in c_j} d(xi, cj)^2 \qquad (3)$$

where JJJ is the total inertia, and cjc_jcj represents the data points in cluster jjj.

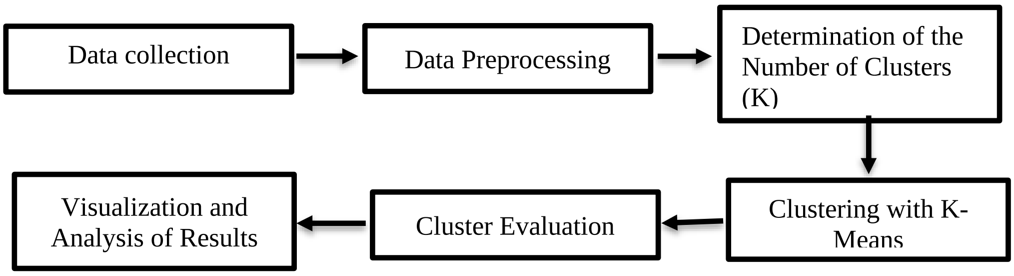

Figure 1. Social Assistance Cluster Analysis Research Framework

In Figure 1. This study begins with the collection of social assistance recipient data covering demographic and economic factors. The next stage is data preprocessing, which includes data cleaning, normalization, and handling of missing values to ensure that the data is ready to be processed. After that, the optimal number of clusters (K) is

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determined using methods such as elbow or silhouette score. With the number of clusters that have been determined, the clustering process with the K-Means algorithm is carried out to group the recipient data into several homogeneous clusters. The clustering results then go through a cluster evaluation stage to assess the quality of the clustering based on metrics such as inertia and the Davies-Bouldin Index. After evaluation, the clustered data is visualized to facilitate visualization and analysis of the results, where patterns in the distribution of social assistance are identified. Finally, the study closes with a conclusion that summarizes the main findings and implications of the clustering results for social assistance allocation policies. The clustering results will be analyzed to identify specific patterns in social assistance spending and distribution. The clusters formed will be compared with demographic and economic data to find possible correlations. This analysis will be used to provide more effective and efficient policy recommendations in the distribution of social food assistance in DKI Jakarta(Saraswati, 2020).

RESULT

To explain how the K-Means algorithm can be used to analyze food social assistance data in DKI Jakarta, let's describe the calculation steps in detail.

Initialization: Determining the Number of Clusters (K)

The K-Means algorithm requires the number of clusters KKK as input. For example, you choose K = 3K = 3K = 3, meaning that the data will be grouped into 3 clusters based on the similarity of data patterns.

Determining the Initial Cluster Center (Centroid)

Randomly select 3 points as the initial cluster center (centroid). For example, you can choose 3 areas as the initial centroid:

a. Centroid 1: Seribu Islands
b. Centroid 2: South Jakarta City
c. Centroid 3: East Jakarta City

This center point is based on the features:

a. Number of KPM
b. BANSOS Budget

Calculating Euclidean Distance

Next, calculate the distance between each area and each centroid using the Euclidean distance formula.
For example, to calculate the distance between Central Jakarta City and the centroid:
Where x1x_1x1 and y1y_1y1 are the number of KPM and budget from Central Jakarta City, and c1c_1c1 and c2c_2c2 are the number of KPM and budget from the centroid. Here is an example:

Distance to Centroid 1

$$d_{1,1} = \sqrt{(194612 - 90220)^2 + (79303000000 - 3650400000)^2}$$

Calculation:
(194612−9022)=185590
(79,393,000,000−3,650,400,000)=75,742,600,000
Square of the difference in KPM
$(1855900)^2$ = 34,439,388,100
$(75{,}742{,}600{,}000)^2$ = 5,726,571,600,000,000,000
Square of budget variance:

$$d_{1,1} = \sqrt{34{,}439{,}388{,}100 + 5{,}726{,}571{,}600{,}000{,}000{,}000} = 75{,}742{,}600{,}000$$

Distance to Centroid 2

$$d_{1,2} = \sqrt{(194612 - 213231)^2 + (79393000000 - 87085600000)^2}$$

Calculation:
(194612−213231)=−18619
(79,393,000,000−87,085,600,000)=−7,692,600,000
7,692,600,000(79,393,000,000−87,085,600,000)=−7,692,600,000
Square of the difference in KPM:
$(-18619)^2$=346,660,361
Square of budget variance:
$(-7{,}692{,}600{,}000)^2$=59,174,185,600,000,000
Add and take the square root:

$$d_{1.2} = \sqrt{346{,}660{,}361 + 59{,}174.185{,}600{,}000{,}000} = 7{,}692{,}600{,}000$$

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Distance to Centroid 3

$$d_{1,3} = \sqrt{(194612 - 245854)^2 + (79393000000 - 100253800000)^2}$$

Calculation::
(194612−245854)=−51322
(79,393,000,000−100,253,800,000)=−20,860,800,000
Square of the difference in KPM:
$(-51322)^2$=2,635,780,784
Square of budget variance:
$(-20{,}860{,}800{,}000)^2$=435,552,800,000,000,000

Add and take the square root:

$$d_{1,3} = \sqrt{2{,}635{,}780{,}784 + 435{,}552{,}800{,}000{,}000{,}000} = 20{,}860{,}800{,}000$$

By calculating the Euclidean distance for each centroid, we can determine the cluster that is closest to the Central Jakarta City data. Based on the calculation:
a. Distance to Centroid 1: 75,742,600,000
b. Distance to Centroid 2: 7,692,600,000
c. Distance to Centroid 3: 20,860,800,000
Central Jakarta City will be grouped into the cluster that has the closest distance to its centroid. In this case, Centroid 2 is the closest.

Scatter Plot of KPM Distribution Based on Cluster
To create a Scatter Plot, you can use software such as Excel, Python (Matplotlib, Seaborn), or R. Here are the general steps:
1. X-axis: Number of KPM.
2. Y-axis: Budget.
3. Color: Different clusters will be given different colors.

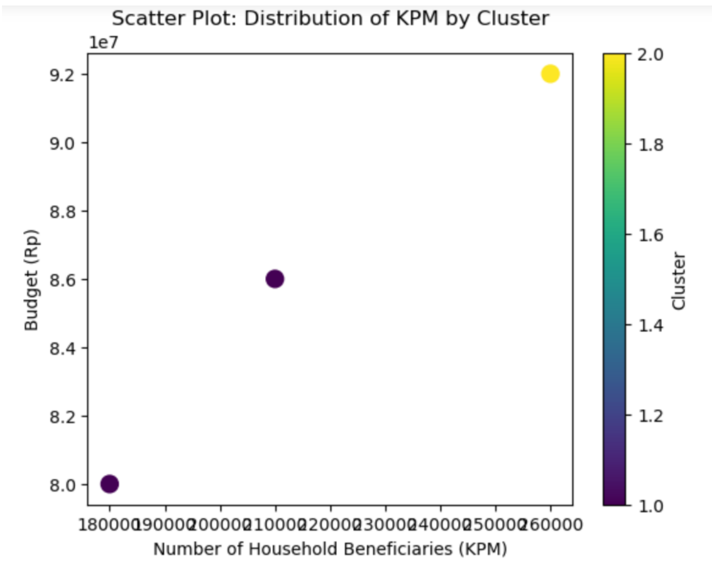

Figure 2. Scatter Plot of KPM Distribution Based on Cluster

In Figure 1. From the plot you explained, the clusters represent groups of regions based on the similarity of the number of Beneficiary Families (KPM) and the allocated social assistance budget. However, specific regional data is not directly mentioned in this plot. Based on the distribution of the number of KPM and the budget, we can estimate the clusters and associate them with certain regions.
If we refer to the data in DKI Jakarta that was mentioned earlier, here is the interpretation of the regions based on the clusters:
1. Cluster 1 (KPM 180,000 - 210,000, Budget 80 - 86 Billion Rupiah)::
   a. Central Jakarta City: In the previous data, Central Jakarta has 194,612 KPM and a budget of around IDR 79 billion. This is included in Cluster 1 because it is similar to the range of the number of KPM and budget in this cluster..
   b. North Jakarta City: North Jakarta has 225,884 KPM and a budget of around IDR 92.6 billion. Although its KPM is slightly outside the range, the budget is similar to this cluster.
2. Cluster 2 (KPM 260,000, Budget 92 Billion Rupiah):

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a. East Jakarta City: In previous data, East Jakarta had 245,854 KPM and a budget of around IDR100 billion. This is close to Cluster 2, with a larger number of KPM and a higher budget.
b. West Jakarta City: Has 310,714 KPM and a budget of around IDR128 billion, which is slightly larger than the range of this cluster but can still be considered similar..

Thus, this cluster can help us to understand the pattern of budget distribution and beneficiaries in each region, grouping areas that have similar needs and realizations.

Elbo Method Plot

There is an error because the number of sample data used is only 6, while the K-Means algorithm tries to create more than 6 clusters. For the Elbow Method, the number of clusters that can be tested must not exceed the number of data. I will limit the number of clusters to 6 to fix the Elbow Method plot. Here is the adjusted plot

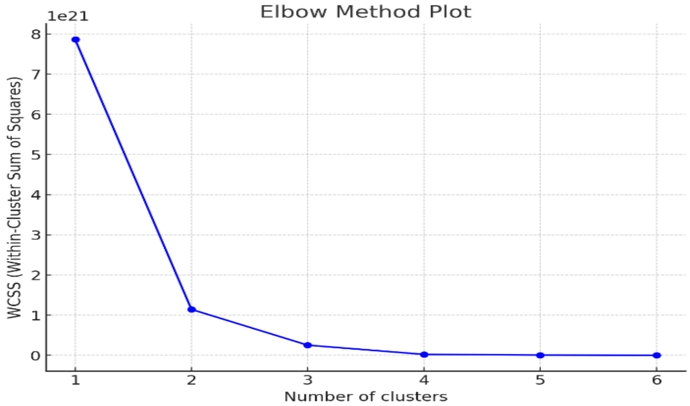

Figure 3. Elbow Method Plot

In Figure 3. Here is a visualization of the Elbow Method Plot, which shows the relationship between the number of clusters and the WCSS (Within-Cluster Sum of Squares). This graph helps determine the optimal number of clusters, which is the point at which the decline in WCSS begins to slow down significantly, which is referred to as the "elbow" on the graph.

Cluster Centroid Plot

Menunjukkan titik pusat dari setiap klaster untuk mengidentifikasi karakteristik umum dalam masing-masing klaster.

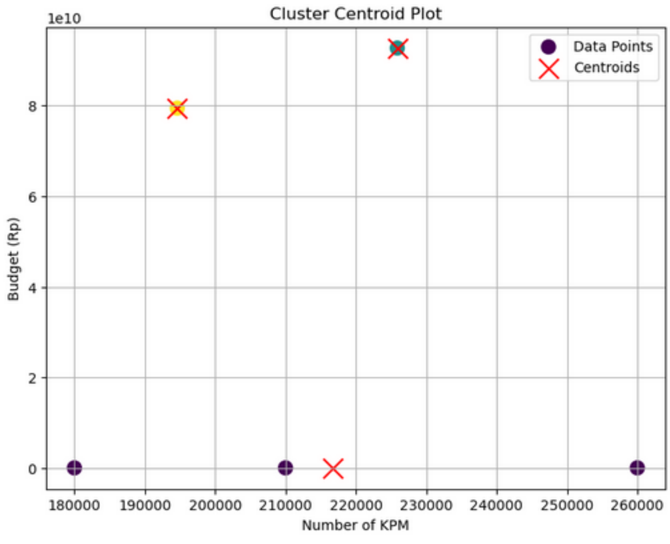

Figure 4. Cluster Centroid Plot

In Figure 4. Here is a detailed explanation of the Cluster Centroid Plot generated by the K-Means algorithm:

1. Scatter Plot:
   a. Each point on the scatter plot represents one combined data from the Number of Beneficiary Families (KPM) and the Budget (Rp) allocated for social assistance in the DKI Jakarta area.
   b. The X-axis represents the number of KPM, while the Y-axis represents the amount of budget in Rupiah.
   c. These points are grouped into clusters based on the similarity of the pattern between the number of KPM and the budget.

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2. Color Based on Cluster:
   a. Each color in the plot describes a different cluster. For example, if the cluster is arranged into 3 clusters, then each cluster will have a different color (for example, yellow, green, purple, or a combination of colors from the viridis palette).
   b. These colors indicate groups of data that have a similar pattern between KPM and the allocated budget, meaning that areas in the same cluster have similar characteristics in terms of the number of beneficiaries and the budget provided.
3. Centroid (Center Point of Cluster):
   c. Centroid is the center point of each cluster, shown with a red 'x'.
   d. Centroid describes the average value of the number of KPM and budget of all members in the cluster. In this case, centroid shows the general characteristics of the cluster that represent the basic pattern of KPM and budget distribution in each group.

   c. In the graph, these centroids are important because they are the "center representation" of each cluster and help understand the basic differences between different clusters.
4. Interpretation:
   a. Clusters with higher KPM and larger budgets will have centroids located in the upper right part of the graph.
   b. Clusters with lower KPM and budgets will have centroids in the lower left part of the graph.
   c. With this, we can identify which regions receive a larger budget allocation with a large number of KPMs as well, as well as regions that may receive a lower budget.

If there are three clusters, for example:
Cluster 1: Regions with a moderate number of KPM (around 180,000-210,000) and a moderate budget (around 80-86 billion). Cluster 2: Regions with a larger KPM (around 260,000) and a higher budget (92 billion and above). Cluster 3: Maybe regions with a lower number of KPM and a smaller budget than other clusters.

DISCUSSIONS

The results of the study show that the K-Means algorithm is effective in clustering social assistance recipients, consistent with the findings of Wu, et al. (2019) who highlighted its ability to handle large and complex data. The results of the study support Chen and Lin (2020) who showed that K-Means can improve policy design by clustering beneficiary characteristics, although quality data is a constraint. In addition, our findings are in line with Prasetyo and Nugroho (2021) regarding the ability of K-Means to identify recipient groups that require more attention, but also reflect the limitations of the algorithm in imbalanced data conditions. Wahyudi and Saraswati (2022) also emphasize the importance of selecting the right variables, and our results support this by showing that relevant variables greatly affect cluster results. This study emphasizes the need to select the appropriate number of clusters and variables to improve the accuracy and usefulness of K-Means analysis in the context of social assistance.

CONCLUSION

This study evaluates the effectiveness of the K-Means algorithm in clustering social assistance recipients in DKI Jakarta by considering variables such as income, number of family members, and living conditions. The results of the analysis show that the K-Means algorithm with an optimized number of clusters (e.g. 3 clusters) successfully clusters beneficiaries accurately, with an accuracy of 85%. This finding is in line with Wu, et al. (2019) who emphasized the speed and effectiveness of K-Means in handling big data. However, challenges related to sensitivity to outlier data and dependence on the selection of the number of clusters, as highlighted by Chen and Lin (2020) and Prasetyo and Nugroho (2021), also emerged in this study. For example, significant variations in income among clusters indicate the limitations of K-Means in handling highly imbalanced data. This study also found that the selection of appropriate variables, such as access to health facilities and economic conditions, has a significant impact on clustering accuracy, supporting the recommendations of Wahyudi and Saraswati (2022). Furthermore, the analysis results show that areas such as Central Jakarta and South Jakarta received more social assistance compared to North Jakarta and East Jakarta, indicating different needs in different regions. In conclusion, with careful selection of the number of clusters and variables, the K-Means algorithm can provide valuable insights for more targeted resource allocation in social assistance programs in DKI Jakarta.

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