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Analysis of K-Means and K-Medoids Algorithms for Grouping Academic Values of Prospective New Students in Selection of Campus Scholarship Recipients

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A B S T R A C T

University of Mahkota Tricom Unggul is one of the private universities (PTS) that prepares various scholarships every year, one of which is the Foundation scholarship. However, so far the University in selecting prospective new students who are eligible to receive Foundation scholarships still uses a conventional model, so it is less effective, efficient, and less professional. As a result, it is less objective in selecting prospective new students in scholarship acceptance. Therefore, an algorithm is needed to group data that is eligible to receive Foundation scholarships using an algorithm. The algorithms used to solve the existing problem are the K-means and Kmedoids algorithms, then analyzed which one is effective in solving the problem. Where both can group data well, but the K-medoids algorithm is more effective in solving than K- Means

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INTRODUCTION

A campus scholarship at a private university (PTS) is financial support provided to students to reduce educational costs and support academic and non-academic achievements. University Of Mahkota Tricom Unggul is one of the private universities (PTS) that offers various scholarships annually, one of which is the Foundation Scholarship. Foundation Scholarships are awarded to prospective new students with academic achievements, which can then support their academic achievements.

However, the university has been using a conventional method to select new students eligible for Foundation scholarships, making it less effective, efficient, and professional. Consequently, the selection process lacks objectivity. This ineffectiveness and professionalism stem from the lack of a consistent algorithm or method for selecting campus scholarship recipients for Foundation scholarships. Therefore, solutions are needed to address or minimize these issues.

The solution to this problem is to apply the K-means and K-medoids algorithms.

The results of these two algorithms will be analyzed to determine which is more effective and efficient.

The reason researchers used these two algorithms is because the K-means algorithm is the most popular and easy-to-understand clustering algorithm, and its application is very broad in various fields. Clustering applications can be attributed to its simplicity of implementation and low computational complexity. In the algorithm initialization process, the user must determine the number of clusters in a given dataset a priori, while the initial cluster centers are selected randomly (Ikotun, 2023) (Marpaung & Siahaan, 2021). The K-means algorithm is a widely used and fundamental clustering technique that uses iterative calculations to divide a given dataset into k clusters. This technique is very effective and adaptive for large datasets. Where each data will be grouped into the nearest cluster (Hu, 2023).

While the K-Medoids algorithm is fast and does not consider the weight of each attribute and the initial clustering center may be in the same cluster (Sun et al., 2023). The K-Medoids algorithm can also be used to efficiently cluster censored data and identify diverse groups with different life time distributions (Marinos et al., 2023).

Based on the existing problems and solutions explained above, it is necessary to group the academic values of prospective students of Mahkota Tricom Unggul University (MTU) into several Clusters, Where Cluster 1 (Very Smart), Cluster 2 (Smart), and Cluster 3 (sufficient), later those in the first cluster are prospective students who are eligible for the foundation scholarship. And also will be analyzed the performance of which algorithm is more suitable to be applied in grouping the academic values of prospective students at MTU.

THEORETICAL REVIEW

Campus Scholarships

Campus scholarships are financial assistance or financial benefits provided by universities to students based on certain criteria such as academic achievement, financial need, or other specific criteria without the need for repayment, to support the continuation or completion of studies (Mulyaningsih et al., 2022).

Academic Values

Academic grades are described as a reflection of the knowledge, skills, and abilities acquired by students in a particular academic field. This assessment is determined through an evaluation process of learning progress over a period. (Bordbar et al., 2025). Academic grades reflect the extent to which a student or institution achieves short-term and long-term educational goals, measured through continuous assessment or Cumulative GPA (CGPA) (Hailu et al., 2024). Previous research has revealed that students conceptualize intelligence as academic values, such as learning, problem-solving, critical thinking, creativity, and spatial reasoning (Oyewole & Thopil, 2023).

Grouping

Grouping, especially used as a technique for analysis for clustering unlabeled data to extract meaningful information, has also driven the development of several clustering algorithms with diverse applications. Furthermore, clustering techniques have been widely used in key industrial sectors related to sustainable development goals, such as manufacturing, transportation and logistics, energy, healthcare, and education (Oyewole & Thopil, 2023).

Knowledge Discovery in Databases (KDD)

Knowledge discovery in databases (KDD) is often equated with the process of extracting hidden information from large databases, even though the two concepts are distinct but interrelated. Data mining is one of the main stages in the KDD process, which generally includes the following steps (Marlina et al., 2022):

Data Selection, data selection from a set of operational data needs to be done before the information mining stage in KDD begins. The selected data that will be used for the data mining process is stored in a file, separate from the operational database.

Pre-processing/Cleaning: Before the data mining process can be carried out, a cleaning process must be carried out on the data that is the focus of KDD. The cleaning process includes removing duplicate data, checking for inconsistencies, and correcting errors in the data, such as typographical errors.

Transformation Coding is the transformation of selected data so that it is suitable for the data mining process. The coding process in KDD is a creative process and is highly dependent on the type or pattern of information being searched for in the database.

Data mining: Data mining is the process of finding interesting patterns or information in selected data using specific techniques or methods. Data mining techniques, methods, and algorithms vary widely. The selection of the appropriate method or algorithm depends heavily on the overall goals and KDD process.

Interpretation/Evaluation: The information patterns generated from the data mining process need to be presented in a form that is easily understood by stakeholders. This stage is part of the KDD process called interpretation. This stage involves examining whether the patterns or information found contradict previously established facts or hypotheses.

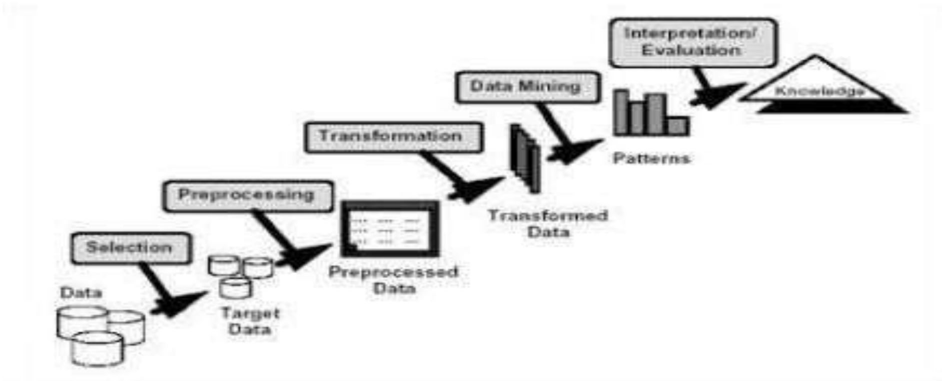

Figure 1. Data Mining Process in Knowledge Discovery in Databases (Shah & Shah, 2023)

K-Means Algorithm

The K-means algorithm is a non-hierarchical clustering algorithm that aims to divide data into K clusters based on characteristic similarities. Each cluster is represented by a center (centroid), while the data is sorted into clusters based on the shortest distance, generally using the Euclidean metric. The initial centroid is randomly determined for a selected number of k clusters. Therefore, the resulting output depends on the initial centroid selection. The K-means algorithm must be run repeatedly to obtain optimal clustering results (Orisa, 2022).

The K-means algorithm is very effective for clustering data, especially when used on large datasets, because it can significantly influence the quality of clustering results.

Steps in the K-means algorithm (Preddy et al., 2023)(Sardar, 2020): 1. Determine the number of clusters

Determine the centroid value (cluster center point) randomly.

Calculating the distance between data or objects and the cluster center using theory Euclid Distancewhich is formulated as follows:

$D (i, j) = \sqrt{(X1 - X1)2+ (X2 - X2)2+ \cdots + (X - X)2 \quad)}$ ....(1)

Where :

D(i, j):Data distance toito the center of the clusterj X

ki : Data toion the data attribute tok

Xkj : Center point tojon the data attribute tok

Data is placed inclusterthe closest.

Centerclusterwill only be determined when all data has been specified incluster closest to the formula:
D=1_ …….(2)
Where :
D : Data set in cluster N :
Number of data in cluster

The flowchart image of the k-means algorithm will be displayed as follows:

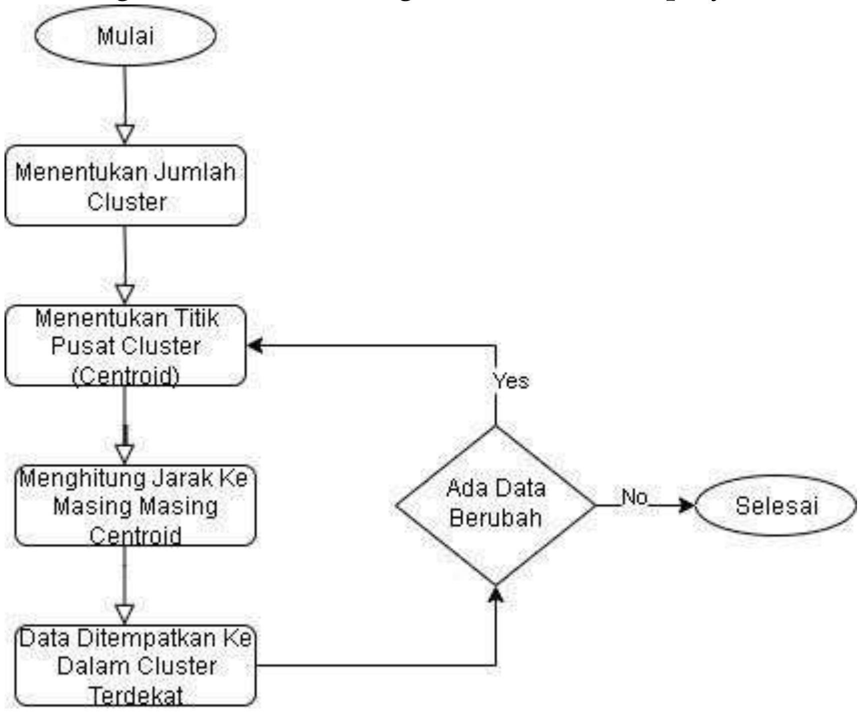

Figure 2. K-Means Algorithm Flowchart The process of determining cluster centers and placing data in clusters is repeated until the data values no longer change.

K-Medoids Algorithm

The K-medoids clustering algorithm is a simple yet effective algorithm that has been applied to solve many clustering problems. Instead of using the average point as the cluster center, K-medoids uses actual points to represent them. A medoid is the object that is most centrally located in a cluster, with the minimum number of distances to other points. K-medoids can represent the cluster center precisely because it is robust against outliers. Using the Whale Optimization Algorithm to reduce the complexity from quadratic to nearly linear, thus allowing K-Medoids to be applied to large datasets while maintaining cluster accuracy (Sureja et al., 2022) (Chenan & Tsutsumida, 2024). The steps of the K-Medoids algorithm are as follows (Shah & Shah, 2023):

Initialize the cluster center as k (number). Determine the centroid value (cluster center point) randomly. Allocate each data (object) to the cluster closest using the distance measurement equation, Euclidean Distance the equation:

D (i, j) = √(X1 − X1)2)
Where :
D(i, j):Data distance toito the center of the clusterj X
ki : Data toion the data attribute tok
Xkj : Center point tojon the data attribute tok

…….(3)

Calculate the distance of each object in each cluster to the new candidate medoids.
Calculate the total deviation (S) by calculating the new total distance value – the old total distance. If S<0, then swap the objects with the cluster data to form a new set of k objects as medoids.
Repeat steps 3 to 5 until there are no changes in the medoids, so that you get the clusters and their respective cluster members.

The flowchart image of the k-means algorithm will be displayed as follows:

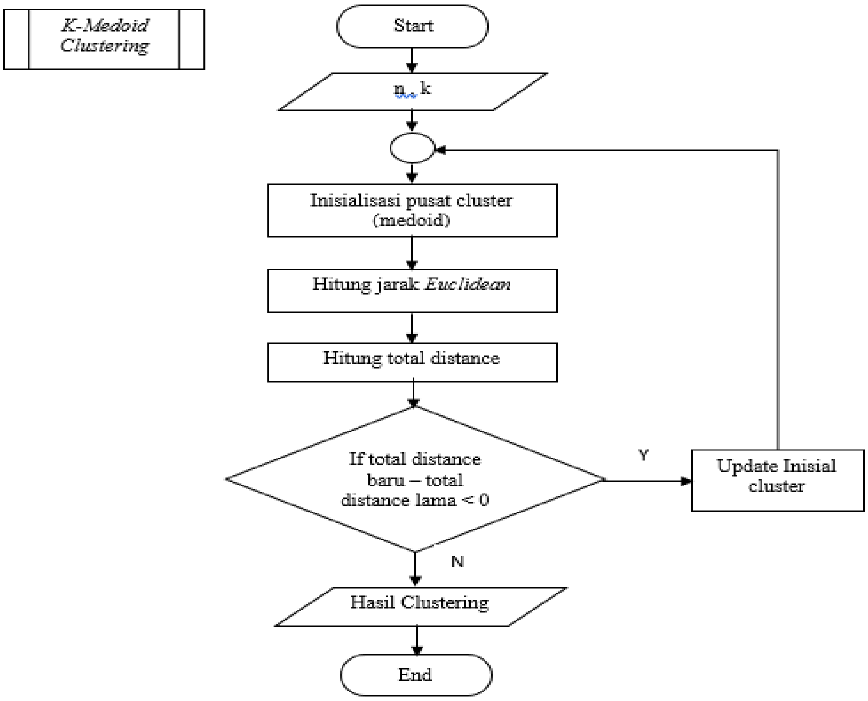

Figure 2. Flowchart Algortima KMedoids

METHODOLOGY

The research began with an analysis of the problem of accepting campus scholarships or foundation scholarships, followed by data collection, including interviews, primary data collection from relevant parties, literature studies on the impact of existing problems, and appropriate algorithms for grouping prospective students' academic grades. The appropriate algorithms for solving the problem are the K-Means and K- Medoids. The results of the two algorithms will be analyzed to determine which is best for grouping students' academic scores into three clusters: C1 (very intelligent), C2 (intelligent), and C3 (fairly intelligent). The stages of this research are as follows:

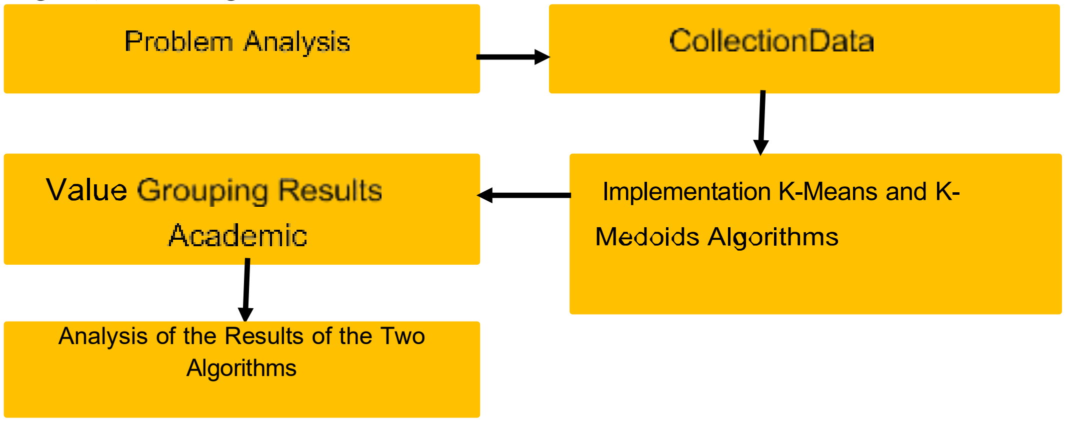

Figure 3. Research Stages

RESERACH RESULTS

This section discusses the calculations of the K-Means and K-Medoids algorithms, and how to group new students' academic scores for campus scholarship acceptance, specifically the Foundation scholarship. The prospective student dataset used in this study is shown in Table 1.

Table 1. Prospective Student Data

No	Name (SKHUN / Prospective Students)	GPA
1	Beautiful Sani Hulu	87.80
2	Ariel Jethro Cahayana	87.84
3	Abib Ardhika Ndraha	81.51
4	Love Revalina Sinaga	80.61
5	Thanks to the Faith of	77.62
6	Talaumbanna Felix Al Vincent	83.85
7	Ancient Geofran	82.90
8	Nathanael Teo Tambunan	87.15
9	Sully Kahila Azzahra	93.17
10	Idamawati Telaumbunua	80.54
11	Yesica Grace Claudia	86.43
12	Radja Arranairi Banuari	83.82
13	Daniel Van Kriston Laoli	79.19
14	Fauza Awwab	85.81
15	Upper Christian	75.85
16	Devin Satria Ramadhan	87.78
17	Chaidir	88.30
18	Linggom Sadrakh Nainggolan	86.35
19	D. Santa Riyani Situmeang	91.16

No	Name (SKHUN / Prospective Students)	GPA
20	**Mawartini Lase**	**82.80**
21	**April Yaman Zai**	**78.77**
22	**M. Dimas Syahputra**	**79.00**
23	**Arman Jaya Waruwu**	**84.40**
24	**Devita Aritonang**	**85.80**
25	**Dedi Darman Halawa**	**84.50**
26	**Silvani Br Sinulingga**	**82.86**
27	**Bright Love Halawa**	**81.07**
28	**Fadya Lara Sati**	**84.50**
29	**Niki Yulia Sari Siregar**	**80.53**
30	**Ridho Purnama Gulo**	**87.07**
31	**Risky Akbar**	**81.31**
32	**Suci Amalia Sari**	**86.31**
33	**Tuti Karina Fa'ana**	**88.69**
34	**Princess Anjelina**	**86.14**
35	**Thomas Rejeki Gulo**	**80.30**
36	**Mr. Agung Aprian**	**79.87**
37	**Lambanda Samuel Sinaga**	**84.87**
38	**M. Luthfi Rangga**	**79.53**
39	**Sari Indah Yani Gea Melvin**	**87.86**
40	**Ekaryawani Zendrato**	**85.36**

K-Means Algorithm Calculation

The steps of the k-means algorithm are as follows: Determining the Initial Cluster Center (Centroid)

The process of obtaining the results of grouping the academic values of prospective new students in the selection of campus scholarships into the categories of Very Smart (C1), Smart (C2), and Sufficient (C3) with the K-Means algorithm, begins with determining the number of cluster centers, namely three cluster centers. The initial cluster centers (centroids) are selected randomly, namely the 8th data as the center of cluster 1 "Very Smart" (87.15), the 20th data as the center of cluster 2 "Smart" (82.8), and the 35th data as the center of cluster 3 "Quite Smart" (80.3). Where the three cluster centers will be summarized into the following table:

Table 2. Initial Cluster Center “Centroid”

No	Cluster	Number of Data	Range SKHUN / GPA	Cluster Center
1	C1 (Very Smart)	8	≥ 87.15	87.15
2	C2 (Smart)	20	82.80 – < 87.15	82.80
3	C3 (Quite Smart)	35	≤ 80.30	80.30

The values at the cluster centers above will be used in the calculations in the first iteration. Calculation of the distance from data 1 to the cluster center The distance calculation will be carried out according to formula 1, where all data will be calculated against the cluster center according to formula 1 above. The following is an example of a calculation between data 1 in table 1 and the cluster center in table 2, below is the calculation. C1 = √(87.15 − 87.8)2= 0.65

C2 = √(82.8 − 87.8)2= 5

C3 = √(80.3 − 87.8)2= 7.5.

Next, calculations are carried out from the 2nd data to the cluster center up to the 40th data.

Placing Data Into the Nearest Cluster

After all the data in table 1 is calculated to the cluster center in table 2 using the Euclidian Distance formula, the calculation results will be set out in the following table:

Table 3. Results Calculation of the Distance of All Data to Each Cluster Center of the First Iteration

No	SKHUN / GPA	C1 Distance	C2 Distance	C3 Distance	Nearest Distance	Nearest Cluster
1	87.80	0.65	5.00	7.50	0.65	Cluster 1
2	87.84	0.69	5.04	7.54	0.69	Cluster 1
3	81.51	5.64	1.29	1.21	1.21	Cluster 3
4	80.61	6.54	2.19	0.31	0.31	Cluster 3
5	77.62	9.53	5.18	2.68	2.68	Cluster 3
6	83.85	3.30	1.05	3.55	1.05	Cluster 2
7	82.90	4.25	0.10	2.60	0.10	Cluster 2
8	87.15	0.00	4.35	6.85	0.00	Cluster 1
9	93.17	6.02	10.37	12.87	6.02	Cluster 1
10	80.54	6.61	2.26	0.24	0.24	Cluster 3
11	86.43	0.72	3.63	6.13	0.72	Cluster 1
12	83.82	3.33	1.02	3.52	1.02	Cluster 2
13	79.19	7.96	3.61	1.11	1.11	Cluster 3
14	85.81	1.34	3.01	5.51	1.34	Cluster 1
15	75.85	11.30	6.95	4.45	4.45	Cluster 3
16	87.78	0.63	4.98	7.48	0.63	Cluster 1
17	88.30	1.15	5.50	8.00	1.15	Cluster 1
…	…	…	…	…	…	…
38	79.53	7.62	3.27	0.77	0.77	Cluster 3

No	SKHUN / GPA	C1 Distance	C2 Distance	C3 Distance	Nearest Distance	Nearest Cluster
39	87.86	0.71	5.06	7.56	0.71	Cluster 1
40	85.36	1.79	2.56	5.06	1.79	Cluster 1

Iteration Process in K-Means Algorithm

After examining Table 3, which shows the results of the first iteration calculation, the data distribution for each cluster is as follows:

- C1 (Very Smart): 16 data
- C2 (Smart): 9 data
- C3 (Quite Smart): 14 data

Determining the New Cluster Center (Centroid)

After all data points are assigned to the nearest cluster in the first iteration, a new cluster center (centroid) is recalculated based on the average value of the data in each cluster according to Formula 2.

For example, since C1 (Very Smart) has 16 data points, the new centroid is calculated as follows:

(87.8+87.84+87.15+93.17+86.43+85.81+87.78+88.30+86.35+91.16+85.80+87.07+86.31+88.69+86.14+87.86+85.36)16=87.5894\frac{(87.8 + 87.84 + 87.15 + 93.17 + 86.43 + 85.81 + 87.78 + 88.30 + 86.35 + 91.16 + 85.80 + 87.07 + 86.31 + 88.69 + 86.14 + 87.86 + 85.36)}{16} = 87.5894

The same calculation method is used to obtain the new cluster centers for C2 and C3.

The results of the new cluster centers in the second iteration are as follows:

Table 4. Cluster Centers of the 2nd Iteration

Cluster	Cluster Center (SKHUN / GPA)
C1 (Very Smart)	87.5894
C2 (Smart)	83.2333
C3 (Quite Smart)	79.6929

The determination of cluster centers is repeated until the data no longer changes. At this stage, the calculation of each prospective student's academic score will again be performed from Table 1 using the new cluster centers from Table 4.

This iterative calculation continues as shown above until the cluster centers stabilize. After five (5) iterations, the grouping of prospective students' academic scores is presented in the table below.

Table 5. Results of Distance Calculation of All Data to Each Cluster Center in the 5th Iteration

No	SKHUN / GPA	C1	C2	C3	Distance	Nearest Cluster
1	87.80	0.2036	3.5108	8.1071	0.2036	Cluster 1
2	87.84	0.1636	3.5508	8.1471	0.1636	Cluster 1
3	81.51	6.4936	2.7792	1.8171	1.8171	Cluster 3
4	80.61	7.3936	3.6792	0.9171	0.9171	Cluster 3
5	77.62	10.3836	6.6692	2.0729	2.0729	Cluster 3
6	83.85	4.1536	0.4392	4.1571	0.4392	Cluster 2
7	82.90	5.1036	1.3892	3.2071	1.3892	Cluster 2
8	87.15	0.8536	2.8608	7.4571	0.8536	Cluster 1
9	93.17	5.1664	8.8808	13.4771	5.1664	Cluster 1
10	80.54	7.4636	3.7492	0.8471	0.8471	Cluster 3
11	86.43	1.5736	2.1408	6.7371	1.5736	Cluster 1
12	83.82	4.1836	0.4692	4.1271	0.4692	Cluster 2
13	79.19	8.8136	5.0992	0.5029	0.5029	Cluster 3
14	85.81	2.1936	1.5208	6.1171	1.5208	Cluster 2
15	75.85	12.1536	8.4392	3.8429	3.8429	Cluster 3
16	87.78	0.2236	3.4908	8.0871	0.2236	Cluster 1
17	88.30	0.2964	4.0108	8.6071	0.2964	Cluster 1
…	…	…	…	…	…	…
38	79.53	8.4736	4.7592	0.1629	0.1629	Cluster 3
39	87.86	0.1436	3.5708	8.1671	0.1436	Cluster 1
40	85.36	2.6436	1.0708	5.6671	1.0708	Cluster 2

In the 5th iteration, the data assignments no longer change, so the calculation process is stopped.

K-Medoids Algorithm Calculation

The dataset used in the K-Medoids algorithm is the same as that used in the K-Means algorithm (Table 1). The object centers for iteration 1 are also the same as in Table 2. The calculation results for the first iteration are shown below:

Table 6. Results of Calculating the Distance of All Data to Each Object Center in the 1st Iteration

SKHUN	Distance	Cluster
40	85.36	

Table 7. Center of Iteration 2

Data	Cluster Center (SKHUN / GPA)
8	O1 (Very Smart): 87.15
24	O2 (Smart): 85.80
35	O3 (Enough): 80.30

Next, a calculation is performed using Formula 2 between the object centers in Table 7 and the prospective student data in Table 1. The results are shown below:

Table 8. Results of Calculation of the 2nd Iteration

No	SKHUN / GPA	C1	C2	C3	Nearest	Cluster
1	87.80	0.65	2.00	7.50	0.65	Cluster 1
2	87.84	0.69	2.04	7.54	0.69	Cluster 1
3	81.51	5.64	4.29	1.21	1.21	Cluster 3
4	80.61	6.54	5.19	0.31	0.31	Cluster 3
5	77.62	9.53	8.18	2.68	2.68	Cluster 3
…	…	…	…	…	…	…
40	85.36	1.79	0.44	5.06	0.44	Cluster 1

Cost Calculation

The total deviation (S) is calculated by finding the difference between the total distance value in the new iteration and the previous iteration.

Iteration	Cost (Σ)
1st	48.67
2nd	50.52

According to the K-Medoids algorithm rule, if the cost in the second iteration is greater than the initial cost, the calculation stops. Thus, the clustering result is determined based on the second cost.

DISCUSSION

This research has systematic and structured steps, where the steps have been used by previous researchers in their research specifically in the fields of data grouping, data mapping, and data classification.

CONCLUSIONS AND RECOMMENDATIONS

The results of this study can be concluded as follows:

1. The k-means and k-medoids algorithms can group data to determine the names of prospective students who are eligible for Foundation scholarships.
2. The k-medoids algorithm is more effective than the k-means algorithm in grouping data.

FURTHER STUDY

As a follow-up to this research, we will develop an application or system in mobile form, so that it can be used more efficiently by all parties who have the authority to enter the system.

REFERENCES

Bordbar, S., Mirzaei, S., Bahmaei, J., Atashbahar, O., & Yusefi, A. R. (2025). Predicting students' academic performance based on academic identity, academic excitement, and academic enthusiasm: evidence from a cross-sectional study in a developing country.BMC Medical Education,25(1). https://doi.org/10.1186/s12909-025-07374-6

Chenan, H., & Tsutsumida, N. (2024).A Scalable k-Medoids Clustering via Whale Optimization Algorithm. http://arxiv.org/abs/2408.16993

Hailu, M., Abie, A., Mehari, MG, Dagnaw, TE, Worku, NK, Esubalew, D., Limenh,

L.W., Delie, A.M., Melese, M., & Fenta, E.T. (2024). Magnitude of academic performance and its associated factors among health science students at Eastern Ethiopia University's 2022.BMC Medical Education,24(1). https://doi.org/10.1186/s12909-024-06296-z

Hu, H. (2023). An Effective and Adaptable K-means Algorithm for Big Data Clusters Analysis.Pattern Recognition,139. https://doi.org/10.1016/j.patcog.2023.109404 Ikotun, A. M. (2023). K-means clustering algorithms: A comprehensive review, variants analysis, and advances in the era of big data.Information Sciences,622, 178–210. https://doi.org/10.1016/j.ins.2022.11.139

Marinos, G., Symvoulidis, C., & Kyriazis, D. (2023). K-Medoids-Surv: A Patients Risk Stratification Algorithm Considering Censored Data.Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics),13589 LNAI. https://doi.org/10.1007/978-3-031-23480-4_11 Marlina, D.,

Lina, N., Fernando, A., & Ramadhan, A. (2018). Implementation of the K-Algorithm

Medoids and K-Means for Clustering of Distribution Areas of Disabilities in Children. CoreIT Journal: Journal of Computer Science and Information Technology Research Results,4(2). https://doi.org/10.24014/coreit.v4i2.4498

Marpaung, P., & Siahaan, RF (2021). Application of the K-Means Clustering Algorithm for Population Density Mapping Based on the Population of Medan City.J-SAKTI (Journal of Computer Science and Informatics).

Mulyaningsih, T., Dong, S., Miranti, R., Daly, A., & Purwaningsih, Y. (2022). Targeted scholarship for higher education and academic performance: Evidence from Indonesia.International Journal of Educational Development,88. https://doi.org/10.1016/j.ijedudev.2021.102510

Orisa, M. (2022). Cluster Optimization in the K-Means Algorithm.SENIATI Proceedings,6(2).

https://doi.org/10.36040/seniati.v6i2.5034

Oyewole, G. J., & Thopil, G. A. (2023). Data clustering: applications and trends.Artificial Intelligence Review,56(7). https://doi.org/10.1007/s10462-022-10325-y

Preddy, …, Marpaung, P., Pebrian, I., & Putri, W. (2023). Application of Data Mining for Population Density Clustering of Deli Serdang Regency Using the K-Means Algorithm.Journal of Computer Science and Information Systems (JIKOMSI),6(2), 64– 70. Sardar, TH (2020). An Analysis of Distributed Document Clustering Using MapReduce Based on K-Means Algorithm.Journal of the Institution of Engineers India Series B,101(6), 641–650. https://doi.org/10.1007/s40031-020-00485-2

Shah, N., & Shah, K. (2023). Introduction to Data Mining. InPractical Data Mining Techniques and Applications. https://doi.org/10.1201/9781003390220-1

Sun, S. J., Chen, L. S., Mei, B. X., Li, T., Ye, X. Q., & Shi, M. (2023). A Weighted k-Medoids Clustering Algorithm Based on Granular Computing.Proceedings - 2023 IEEE 10th International Conference on Cyber Security and Cloud Computing and 2023 IEEE 9th International Conference on Edge Computing and Scalable Cloud, CSCloud-EdgeCom 2023. https://doi.org/10.1109/CSCloud-EdgeCom58631.2023.00032

Sureja, N., Chawda, B., & Vasant, A. (2022). An improved K-medoids clustering approach based on the crowd search algorithm.Journal of Computational Mathematics and Data Science,3. https://doi.org/10.1016/j.jcmds.2022.100034