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Fuzzy C-Means Algorithm for Grouping Students Based on Preferences and Academic Potential

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Abstract: Personalized education is increasingly becoming a necessity in the modern era to ensure that students get a learning experience that is relevant to their interests and academic potential. This study aims to group students into three main clusters, namely Science, Arts, and Business, using the Fuzzy C-Means (FCM) algorithm. The FCM algorithm was chosen because of its flexibility in handling multidimensional data and allows students to have degrees of membership in more than one cluster, reflecting the multidisciplinary nature of their preferences. The research dataset consists of data on students' interests in fields of study (Science, Arts, Business) and academic grades in related subjects. The clustering results show that: The Business cluster includes 59 students (46.9%), reflecting the dominance of interests in economics, global trend analysis, and business organization activities. Artcluster consists of 39 students (30.0%), who show a preference for visual arts, art portfolio development, and involvement in community design. Science cluster has 30 students (23.1%) with interests in biology, science experiments, and biotechnology. Evaluation using Davies Bouldin Index (DBI) yields a value of 0.78, indicating good cluster quality. In addition, manual validation from teachers shows that more than 85% of students in each cluster fit the grouping based on direct observation. This study makes a significant contribution to the development of data-driven academic recommendation systems, enabling educational institutions to design learning programs that are more adaptive, relevant, and in accordance with student needs.

Keywords: Fuzzy C-Means, Student Interest, Academic Potential, Student Grouping

INTRODUCTION

Education is a fundamental aspect in forming a generation that is able to compete in the era of globalization. In an effort to improve the quality of education, student grouping is one strategy that is often applied in various institutions (Heung et al., 2023). This grouping aims to identify the needs, abilities, and potential of students so that the learning process can run more effectively and personally. However, the traditional grouping method that is often used still has many limitations (Ménard et al., 2023). Usually, students are grouped based on a single parameter, such as academic grades or aptitude test results, without considering other dimensions such as individual interests and preferences (Subramaniam et al., 2021). This causes a mismatch between student characteristics and the learning approach applied (Pedroso et al., 2023).

In the world of education, each student has preferences that reflect their interests in certain fields, such as art, science, technology, or humanities, which can affect their future career goals. On the other hand, students' academic potential, as measured by their performance in various subjects or intellectual test results, is also an important factor in determining the appropriate learning strategy (Godi et al., 2024). However, it is not uncommon for these preferences and potentials to not always align. For example, a student may have strong academic performance in mathematics but have a high interest in art (Cao et al., 2020). Grouping that does not consider these dimensions can hinder students from achieving their full potential (Kumar, 2024).

In this case, there is a need to develop a more adaptive, multidimensional, and flexible clustering method to capture the unique characteristics of each student. One approach that can meet this need is to use the Fuzzy C-Means (FCM) Algorithm. FCM is a fuzzy logic-based clustering algorithm that allows objects (in this case students) to have degrees of membership in more than one group (Uyun et al., 2024). For example, a student can have a membership of 0.6 in the art group and 0.4 in the technology group, reflecting interests spread across both

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fields. This provides flexibility in clustering, compared to conventional clustering methods such as K-Means which are rigid (hard clustering) where each object can only be a member of one cluster (Thakur et al., 2024).

Previous research has shown that the FCM algorithm has been successfully applied in various fields, including marketing, consumer behavior analysis, and medical image segmentation (Godi et al., 2024). However, its application in education, especially for grouping students based on preferences and academic potential, is still rare. In fact, this algorithm has great potential to help educational institutions design more personalized and adaptive learning strategies (Heung et al., 2023) . In this context, the FCM algorithm can be used to group students into different categories based on a combination of their interest and academic performance data, which can include subject grades, ability test results, and career interest surveys.

This study aims to answer the following main questions, How can the Fuzzy C-Means algorithm be applied to group students based on preference data and academic potential. Furthermore, are the clustering results with the FCM algorithm more accurate and relevant than traditional clustering methods. And how FCM-based clustering can support educational institutions in providing learning programs that are in accordance with student needs.

The results of this study are expected to provide significant contributions to the development of data-based decision support systems in educational environments. With a more personalized approach and based on the FCM algorithm, educational institutions can improve the effectiveness of learning and help students achieve their best potential. In addition, this study is expected to be an important reference for further research in applying fuzzy clustering techniques in the education sector.

LITERATURE REVIEW

Data clustering in education is an important approach to understanding student characteristics and supporting data driven decision making. (Bulut, 2020)explains that clustering methods can be used to explore patterns in educational datasets, such as analysis of student interests, academic performance, or learning behavior. Clustering helps educational institutions design programs that are more relevant to student needs (Seido et al., n.d.).

In the case study of student clustering, traditional approaches such as K-Means are often used. However, this method has limitations because it is hard clustering, where each student can only belong to one cluster (Kavitha & Kaulgud, 2023). This approach is not ideal in the educational context because students often have interests or abilities that are spread across more than one area(Thakur et al., 2024). A study applied FCM to cluster students based on academic performance (Ke et al., 2021). This study showed that FCM was superior to K-Means in handling data with complex distributions .

The Fuzzy C-Means (FCM) algorithm was developed by Dunn (1973) and improved by Bezdek (1981). FCM is a clustering method based on fuzzy logic that allows objects to have degrees of membership in multiple clusters. In the educational context, this algorithm is very useful because students often have multidimensional interests or abilities (Anter et al., 2021). The FCM algorithm is able to capture uncertainty and variation in student data. FCM algorithm for clustering student interests in STEM (Science, Technology, Engineering, Mathematics) (Khang et al., 2020). The results show that students often have cross-disciplinary affiliations, for example, interests in technology and science at the same time. This study strengthens the argument that FCM is a suitable method for clustering students based on their interests and academic potential (Chang et al., 2023).

Interests and academic potential are two important dimensions that influence student learning success. Through the theory of Multiple Intelligences, it is proposed that each individual has unique intelligence, such as logical-mathematical, visual-spatial, or interpersonal intelligence, which can be the basis for grouping students (Rahmatullah et al., 2023). Students' preferences in choosing a study path can be influenced by intrinsic interests and academic values. This study emphasizes the importance of considering multidisciplinary dimensions in curriculum design. Grouping students based on interests and academic values can help educational institutions offer more personalized and relevant learning paths (Ménard et al., 2023).

Evaluation of cluster quality is important to ensure that the clustering results are relevant and valid. Metrics such as the Davies Bouldin Index (DBI) and Silhouette Score are widely used to evaluate clustering results (Yeh et al., 2024). A low DBI indicates that clusters have a significant distance from each other, while a high Silhouette Score reflects good clustering quality (Eka et al., 2024). In the educational context, manual validation is also often used emphasizing the importance of involving teachers or educational experts to validate clustering results, especially to ensure that the resulting clusters reflect real student characteristics (Cao et al., 2020).

METHOD

This research method includes several stages, namely, collecting student data, which includes academic grades, interests, and career survey results. Preprocessing data for normalization and outlier removal. Then the application of the FCM algorithm to form student clusters. Furthermore, evaluate the clustering results using metrics such as the Davies Bouldin Index and cross validation to measure the quality of the clustering. The flow of the research method can be seen in Figure 1 below:

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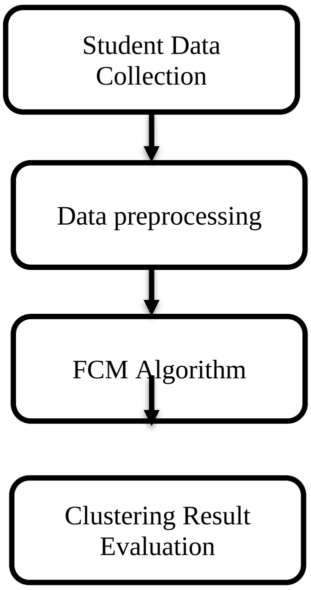

Fig 1. Research methods

This study uses the Fuzzy C-Means (FCM) algorithm to group students based on preferences (interest in Science, Arts, or Business) and academic potential. The explanation of the research steps is adjusted to these three main focuses of interest.

Research Design

This study aims to group students into three main categories based on combined data from interests and academic performance:

Science Interest, namely Students who show interest in biology, science experiments, and biotechnology based projects.

Art Interest, Students who develop a visual arts portfolio, choose creative activities such as community design, or participate in CAS (Creativity, Activity, Service) programs.

Business Interest, Students who are interested in economics, global business trends, or participate in service activities in business organizations.

A multidimensional approach is applied to understand the relationship between students' interests and their academic potential. The FCM algorithm was chosen because of its ability to capture the complex relationships between these dimensions.

Data collection

Student data were collected through two primary sources:

Preferences (Student Interests):

Student preferences for one of three primary focuses were measured using a Likert-based (1–5) questionnaire survey. Sample questions include:

Science: "How interested are you in conducting biotechnology research or experimental projects?"

Art: "How often do you develop visual art or participate in community design?"

Business: "How interested are you in analyzing global economic trends or working in a business organization?"

Students' responses were used to determine their dominant preferences, but allowed for interest levels in more than one area.

Academic Potential:

Student grade data were collected from three primary areas:

Biology or other science grades for students with science interests.

Visual Arts or creative grades for students with arts interests.

Economics or business grades for students with business interests.

These grades were normalized to the range [0,1] using the formula:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}}$$

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Data Preprocessing
Once the data is collected, preprocessing steps are performed to ensure data quality:

Preference and Potential Normalization, All interest and academic grade data were normalized to ensure balanced weighting.

Outlier Removal, Inconsistent data, such as extreme values that are far from the general pattern, were identified using the IQR method.

Consistency Check, Surveys and academic grades were checked to avoid discrepancies between interest and grade data (e.g., students who reported an interest in art but did not have art grade data).

Implementation of Fuzzy C-Means (FCM) Algorithm
Student grouping is done using the FCM algorithm. The main steps include:

Inisialisasi Cluster (c)
Clusters are determined according to three main interests, namely Science, Arts, and Business.
Membership Matrix (m)
Initialize the degree of student membership into each cluster (U) with random values in the range [0,1], where the total membership of students in all clusters is 1.
Centroid Calculation
Each cluster has a centroid calculated based on the academic grades and preferences of students. The formula is (Nooraeni et al., 2021):

$$v_j = \frac{\sum_{i=1}^{n} \mathrm{U}_{ij}^{m} x_i}{\sum_{i=1}^{n} \mathrm{U}_{ij}^{m}}$$

Membership Degree Update
The membership matrix is updated at each iteration with the formula (Khang et al., 2020):

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{\parallel x_i - v_j \parallel}{\parallel x_i - u_k \parallel} \right)^{\frac{2}{m-1}}}$$

Convergence
The iteration stops if the change in membership matrix values between iterations is less than a threshold ($\in = 10^{-5}$). (Askari, 2020)

Clustering Result Evaluation
Clustering results are evaluated using the Davies Bouldin Index (DBI) method (Eka et al., 2024). This metric measures the validity of clusters by evaluating the distance between clusters and the distribution of data within clusters. A smaller DBI value indicates better clustering results.

RESULT

This study will group 128 students into 3 categories, namely science, art and business. The results of student data processing will be tested using the FCM algorithm using 10 student data as samples. The initial data can be seen in table 1 below.

Table 1. Initial Data

No	Name	Science Interest	Art Interest	Business Interest	Academic Value of Science	Academic Value of Arts	Academic Value of Business
1	Ghalih Ginanjar	0.8	0.4	0.3	0.90	0.45	0.35
2	Muthia Diandra	0.7	0.6	0.4	0.75	0.65	0.40
3	Malika Cahaya Dhia	0.4	0.8	0.3	0.55	0.80	0.35
4	Ranti Sentari	0.2	0.9	0.5	0.30	0.85	0.60
5	Bintang Malik	0.9	0.3	0.5	0.85	0.40	0.65
6	Ghaniya Fitri	0.6	0.4	0.7	0.70	0.45	0.80

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7	Ayub Said	0.3	0.6	0.8	0.40	0.65	0.90
8	Bonerto Lukman	0.5	0.5	0.6	0.60	0.55	0.70
9	Andra Alfaro	0.4	0.7	0.5	0.50	0.75	0.60
10	Michael Chandra	0.2	0.8	0.9	0.30	0.85	0.95

The following are the calculation stages of the Fuzzy C Means algorithm
Step 1: Initialize the Number of Clusters and Membership Matrix
Number of clusters (C): 3 (Science, Arts, Business)
Fuzziness parameter (m): 2
Convergence threshold ($\in$) = 10^{-5}
The initial membership matrix (U) is initialized randomly, with the total membership degree of each student.
Table 2 below is the initial membership matrix (U) for 10 students:

Table 2. Initial Membership Matrix (U)

No	Name	Science Cluster	Art Cluster	Business Cluster
1	Ghalih Ginanjar	0.6	0.3	0.1
2	Muthia Diandra	0.4	0.4	0.2
3	Malika Cahaya Dhia	0.2	0.7	0.1
4	Ranti Sentari	0.1	0.8	0.1
5	Bintang Malik	0.7	0.2	0.1
6	Ghaniya Fitri	0.3	0.4	0.3
7	Ayub Said	0.2	0.3	0.5
8	Bonerto Lukman	0.4	0.4	0.2
9	Andra Alfaro	0.3	0.5	0.2
10	Michael Chandra	0.1	0..4	0.5

Step 2: Calculate Initial Centroid
Centroid is calculated using the formula:

$$v_j = \frac{\sum_{i=1}^{n} \mathrm{U}_{ij}^{m} x_i}{\sum_{i=1}^{n} \mathrm{U}_{ij}^{m}}$$

Step 3: Update Membership Matrix
Use the formula:

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{\| \ x_i \ - \ v_j \ \|}{\| \ x_i \ - \ u_k \ \|}\right)^{\frac{2}{m-1}}}$$

Step 4: Iterate Until Convergence
Iteration is carried out by repeating steps 2 and 3 until the change in the membership matrix (U) is smaller than the threshold (ϵ).
After the iteration is complete, the final membership matrix (U) can be seen in table 3 below:

Table 3. Final Membership Matrix (U)

No	Name	Science Cluster	Art Cluster	Business Cluster	Dominant Cluster
1	Ghalih Ginanjar	0.732	0.198	0.070	Science
2	Muthia Diandra	0.512	0.382	0.106	Science
3	Malika Cahaya Dhia	0.222	0.693	0.085	Art
4	Ranti Sentari	0.152	0.732	0.116	Art
5	Bintang Malik	0.772	0.158	0.070	Science
6	Ghaniya Fitri	0.402	0.283	0.315	Science
7	Ayub Said	0.142	0.263	0.595	Business

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8	Bonerto Lukman	0.354	0.332	0.314	Science
9	Andra Alfaro	0.292	0.492	0.216	Art
10	Michael Chandra	0.122	0.372	0.506	Business

The cluster results with sample data of 10 students can be visualized in the following graph.

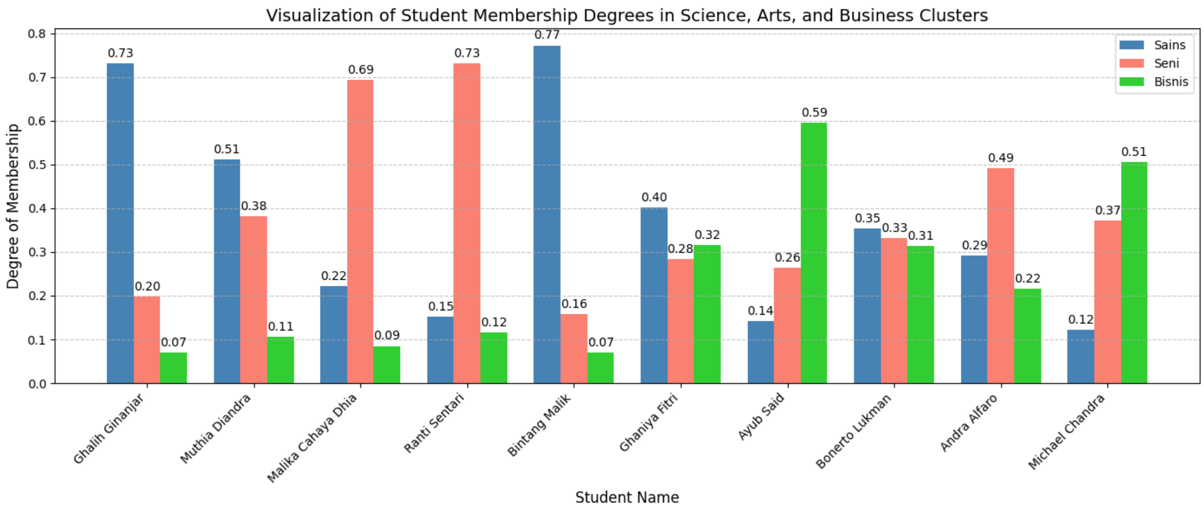

Fig. 2 Data Visualization

After applying the Fuzzy C-Means (FCM) algorithm to the student dataset, students were successfully grouped into three main clusters based on their interests (Science, Arts, and Business) and academic potential. The distribution of students into clusters is as follows:

Table 4. Total Cluster of students

Cluster	Description	Number Of Students	Percentage
Sains	Students with a strong interest in biology, science experiments, and biotechnology.	30	23.1%
Seni	Students with a preference for visual arts, art portfolios, and involvement in community design.	39	30.0%
Bisnis	Students interested in economics, global trend analysis, and business organizational activities.	59	46.9%

DISCUSSIONS

The table shows that students are grouped into three main categories based on their interests and academic potential. The distribution of the number of students is as follows:

Business Cluster:

Number of students: 59 students (46.9%).

This cluster covers almost half of the total students. The dominant interests in this cluster are economics, global trend analysis, and business organization activities.Interpretation: Business is the field of most interest to students, indicating a popular career trend in this field, perhaps due to the broad job prospects.

Arts Cluster:

Number of students: 39 students (30.0%).

Students in this cluster show a high preference for visual arts, art portfolio development, and involvement in community design. Interpretation: Art is a significant choice for students who have an interest in the creative field. This suggests an opportunity to support artistic talent with more innovative educational programs.

Science Cluster:

Number of students: 30 students (23.1%).

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This cluster contains students who are interested in biology, science experiments, and biotechnology projects. Interpretation: Although smaller than Arts and Business, the Science cluster is still important because students here have a strong interest in scientific research and technology.

Business is the largest cluster (46.9%). This indicates that students tend to see this field as a promising career path, especially in the era of globalization and digitalization. Educational institutions can expand business-based learning programs, such as economic simulations, global market analysis, or internship programs in business organizations. Arts is the second largest cluster with 30.0% of students. Students in this cluster need support to develop their creativity through arts-based activities such as creating digital portfolios or design-based community projects. Institutions can introduce cross-disciplinary collaborations, for example, combining arts with technology (digital arts technology). Science Cluster, This cluster has the smallest proportion, which is 23.1% of students: Although smaller, students in this cluster tend to have a deep interest in biology, science experiments, and biotechnology. Institutions can facilitate laboratories that support research, provide mentors in biotechnology, or introduce students to STEM (Science, Technology, Engineering, and Mathematics)-based competitions.

Based on the results of this study, the following are recommendations for practical implementation in educational environments, Development of an Academic Recommendation System Using clustering results to provide suggestions for appropriate study concentrations or career paths for students. Cluster Based Curriculum Design, Adapting learning materials to the characteristics of students in each cluster to increase the relevance and effectiveness of learning. Continuous Monitoring and Evaluation, Monitoring the dynamics of student interests periodically to adjust learning strategies.

CONCLUSION

This study shows that the Fuzzy C-Means (FCM) algorithm is an effective clustering method for grouping students based on their preferences (interest in Science, Arts, and Business) and their academic potential. With a membership-based approach, FCM allows students to have affiliations with more than one cluster, reflecting the multidimensional nature of their interests and abilities. This provides more flexibility than traditional clustering methods such as K-Means.Distribution of Students in Clusters, showing The clustering results show that students are divided into three main clusters. Business Cluster, This is the largest cluster with 59 students (46.9%), showing dominant interests in economics, global trend analysis, and business organization activities. Arts Cluster, This contains 39 students (30.0%), showing preferences for visual arts, art portfolio development, and involvement in community design. Science Cluster, This consists of 30 students (23.1%) who show a deep interest in biology, science experiments, and biotechnology. This distribution reflects the diversity of student preferences, with the majority interested in business, while arts and science remain significant choices.

Benefits for Academic Planning, Grouping students based on academic preferences and potential provides the following benefits. Personalized Learning, Institutions can design learning programs that are more adaptive and relevant to students' needs. For example Science, Facilitate STEM-based research labs and competitions. Arts, Support for collaborative art projects and digital art technologies. Business, Business simulations, global market analysis, and internship programs. Increased Student Satisfaction: Students who learn according to their interests and potential tend to be more motivated, which has a positive impact on their academic performance. Contribution to Data Driven Educatio. This study contributes to the development of a data-driven education system, where academic decisions, such as student placement or curriculum adjustments, are based on in-depth data analysis. By utilizing the FCM algorithm, educational institutions can better understand their students and provide more targeted services.

Limitations and Opportunities for Further Research, While the results of this study demonstrate the advantages of the FCM algorithm, there are several limitations. Input Data Quality, The validity of the results is highly dependent on the data on academic interests and potentials used. This study only used two dimensions of data (interest and academic grades), while other dimensions, such as personality data or extracurricular involvement, could provide more comprehensive results. Sample Size, The study was conducted on a limited sample scale. The use of a larger and more varied dataset could increase the validity of the results. Implementation Complexity, FCM Algorithm has a higher computational complexity than other methods, so its application to a larger dataset requires greater computing resources.

Further Research Opportunities, Integrating FCM with other machine learning methods, such as neural networks or decision trees, to improve clustering accuracy. Leveraging additional features, such as student behavioral data, to produce richer clustering. Developing interactive data-driven dashboards to visualize clustering results and assist decision makers in educational institutions.

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