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Research paper

Evaluation of Civil Engineering Students' Academic Performance Using Fuzzy C-Means Clustering

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ABSTRACT

Background: Students' academic performance is a crucial indicator of their mastery of core competencies obtained throughout the learning process in higher education. These competencies become an essential benchmark, not only for academic evaluation, but also for the industry that expects graduates to meet professional standards. Therefore, an objective and data-driven evaluation method is needed to identify students' academic performance and support academic decision-making.

Methods: This study employs the Fuzzy C-Means (FCM) clustering method as an educational data mining technique to classify civil engineering students based on their academic results. Three key competency areas are used in this study, i.e., Structure and Material (SM), Geometry and Transportation (GT), and Construction Management (CM). A total of 221 students were analysed, exceeding the minimum sample size. The clustering process was performed using multiple cluster models (three, four, and five clusters), and the silhouette coefficient was used to evaluate the quality and accuracy of the clusters.

Results: The findings reveal that the three-cluster model provides the most representative structure, showing the highest silhouette coefficient value compared with others. This indicates that three clusters offer the most appropriate grouping for evaluating academic performance. Cluster 1 represents students with excellent academic achievement, cluster 2 consists of students with good performance, and cluster 3 represents students with concerning academic performance requiring additional academic support.

Conclusion: Overall, the study concludes that the three-cluster model, consisting of an excellent, good, and concerning performance group, offers the most accurate and representative evaluation of civil engineering students' academic performance. These results provide valuable insights to design targeted interventions, enhance learning support, and optimize curriculum alignment to ensure that students achieve the competencies required before entering the professional field.

INTRODUCTION

Technological advancements demand that graduates possess industry-relevant competencies aligned with their respective fields of study. Consequently, higher education institutions must continuously evaluate and update their academic curricula to ensure that student competencies meet industry expectations. One essential component of this process is the periodic and comprehensive evaluation of students' academic performance (Rachmatika & Bisri, 2020).

Student academic performance reflects the extent to which learners have mastered the core competencies required in their study programs. These competencies are developed through learning activities and represent the students' readiness to enter the professional environment (Kusumastuti, 2020; Putu & Putra, 2021). For instance, civil engineering students are expected to excel in competencies related to construction, materials, structures, and infrastructure (Aminah et al., 2023; Saputra et al., 2023). Mastery of these competencies also serves as a benchmark for industries when evaluating the quality of graduates (Saputra et al., 2022a).

Despite the availability of various academic data in higher education institutions, traditional evaluation approaches often rely on descriptive summaries or grade-based assessments that are limited in identifying deeper performance patterns among students. This creates a research gap, where institutions lack data-driven methods capable of uncovering the multidimensional characteristics of student achievement. More specifically, there is a need for analytical techniques that can classify students into meaningful academic performance groups to support targeted academic interventions.

One of the approaches to evaluate student academic performance is data exploration using data mining techniques, also known as educational data mining (Križanić, 2020). This approach is feasible when various educational data exist in a large database, aiming to support learning processes and activities (Nafuri et al., 2022). Every higher education institution undoubtedly possesses a database storing each student's academic track record. One such database commonly found in higher education institutions is the learning management system used for each course. The rich information within these databases already represents a form of educational data mining that can be researched and utilized for control and evaluation purposes (Sarker et al., 2024). This allows for a comprehensive view of overall competencies, thereby enabling the mapping of student academic performance.

In this study, student academic performance is evaluated using three key variables representing the core competencies of civil engineering students: Structure and Material (SM), Geometry and Transportation (GT), and Construction Management (CM). These variables serve as the basis for forming clusters using the Fuzzy C-Means (FCM) clustering algorithm.

Building on the existing gap and the need for a more robust evaluation mechanism, this research aims to classify student academic performance into meaningful groups using FCM clustering. The findings are expected to provide higher education administrators with data-driven recommendations to strengthen academic monitoring, enhance learning support, and improve curriculum alignment with industry needs.

METHODS

This study uses a quantitative research design because it analyses numerical academic data derived from students' competency-based course results. The research employs a descriptive quantitative approach, aiming to identify patterns, classify student academic performance, and generate objective groupings based on measurable indicators. Within this quantitative framework, the study utilizes educational data mining techniques, specifically the Fuzzy C-Means clustering algorithm, to explore and classify academic performance data (El Aissaoui et al., 2019).

The use of the Fuzzy C-Means algorithm is appropriate for this study because no predefined categories of student academic achievement existed before analysis. Fuzzy C-Means clustering is utilized because it can cluster student data using criteria that serve as a reference for evaluating academic performance (Syahputra & Hutagalung, 2022). Given the absence of pre-existing student groupings based on academic achievement, the fuzzy logic concept within this method is highly suitable for application (Al-Abdaliah et al., 2020). With Fuzzy C-Means clustering, researchers can group data using a distance function to maximize or minimize data similarity among the formed clusters (Bezdek et al., 1984). In other words, the resulting clusters contain data with similarities determined by the most dominant membership value, while also ensuring cluster heterogeneity (Syahputra & Hutagalung, 2022).

This study combined both purposive sampling and simple random sampling to determine the research respondents (Devore, 2016). Purposive sampling was used to establish the respondents' background, specifically final-year students from the Civil Engineering Department at Politeknik Negeri Jakarta. This selection considered that final-year students would have acquired various essential core competencies before graduating and entering the professional world. Subsequently, the researchers used simple random sampling to obtain the required number of respondents. The number of respondents was determined using Slovin's formula (Sugiyono, 2014), as follows:

$$n = \frac{N}{1 + N(e)^2} \tag{1}$$

With a population (N) of 271 students and a 5% margin of error (e), the researchers targeted the involvement of 162 students as research respondents. Once the minimum number of respondents was met, the researchers collected research data in the form of students' academic results on the core competencies they acquired.

The researchers divided the core competencies for civil engineering students into three areas: Structure and Material (SM), Geometry and Transportation (GT), and Construction Management (CM) (Amalia et al., 2021a). The academic results referred to here are the final grades students obtained in all courses related to these three competencies.

After the data were collected, the researchers proceeded to the data analysis phase using the Fuzzy C-Means clustering algorithm. The Fuzzy C-Means algorithm involves the following steps (Al-Abdaliah et al., 2020; Bezdek et al., 1984):

1. Determine:
    a. Matrix X with dimensions of $n \times p$, where n represents the number of data points to be clustered and p represents the number of variables (or cluster formation criteria using fuzzy logic)

b. Number of clusters (C) that will be formed with the minimum number of clusters is 2
c. Weighting factor (w) which the general value of the weighting factor is 2
d. Maximum number of iterations
e. The termination criterion value (ξ) which is a very small positive value.

2. Form the initial partition matrix as follows:

$$U = \begin{bmatrix} u_{11}(x_1) & u_{12}(x_2) & \cdots & u_{1n}(x_n) \\ u_{21}(x_1) & u_{22}(x_2) & \cdots & u_{2n}(x_n) \\ \vdots & \vdots & \ddots & \vdots \\ u_{C1}(x_1) & u_{C2}(x_2) & \dots & u_{Cn}(x_n) \end{bmatrix} \quad (2)$$

Note: the membership values for the initial partition matrix are determined randomly.

3. Determine the centroid (v) of each cluster as follows:

$$v_{ij} = \frac{\sum_{k=1}^{n} (u_{ik})^w \cdot x_{kj}}{\sum_{k=1}^{n} (u_{ik})^w} \quad (3)$$

4. Determine the new membership values of each data towards each cluster based on the following formula:

$$u_{ik} = \left[\sum_{j=1}^{c} \left(\frac{D(x_k, v_i)}{D(x_k, v_j)} \right)^{\frac{2}{w-1}} \right]^{-1} \quad (4)$$

Note: $D(x_k, v_i) = \left[\sum_{j=1}^{m} (x_{kj} - v_{ij}) \right]^{\frac{1}{2}}$

5. Determine the termination criterion value (ξ) based on the difference of the partition matrix between the current and previous iterations, as follows: $\Delta = \left\| \mathbf{U}^{\mathbf{t}} - \mathbf{U}^{\mathbf{t-1}} \right\|$

The iteration process stops when $\Delta \leq \xi$. However, if $\Delta > \xi$, then the next iteration is performed $(t = t + 1)$, and the iteration repeats from step three. The value of Δ can be determined by taking the largest element from the absolute difference between $u_{ik}(t)$ and $u_{ik}(t-1)$. Once the iteration stops, data will be clustered based on their highest membership values within the respective groups.

After the clusters were formed, the researchers evaluated them to determine the accuracy level of the clustering process, ensuring the quality of the resulting clusters for research findings. The cluster accuracy measurement method used in this study, which involves determining the accuracy of time series grouping, is the silhouette coefficient method. The criteria for calculation results using the silhouette coefficient method are as follows (Rochman et al., 2022):

Table 1.
Silhouette Coefficient (SC) and Its Criteria

***Silhouette Coefficient* (SC)**	**Criteria**
$0.7 \leq SC \leq 1$	Close Structure
$0.5 \leq SC < 0.7$	Medium Structure
$0.25 \leq SC < 0.5$	Tensile Structure
$SC < 0.25$	Unstructured

RESULTS AND DISCUSSION

The data collection process yielded 221 student respondents. This number exceeded the target calculated using Slovin's formula, allowing the research to proceed to the initial cluster determination phase. Researchers utilized three clustering models based on the number of clusters formed: three clusters, four clusters, and five clusters. The aim of forming diverse clustering models was to identify the most representative number of clusters reflecting the student population. The parameters used in this study are presented in Table 2.

Table 2.
Research Parameter

Parameter	Symbol	Value
Number of data	n	221
Number of variables	p	3
Number of clusters	C	$3;\ 4;\ 5$
Maximum iterations	t_{max}	1000
Weighting factors	ω	3
Termination criterion value	ξ	10^{-6}

Cluster formation using the Fuzzy C-Means clustering algorithm involves processing the academic competency score data from the respondents and the algorithm parameters listed in Table 2. The clustering algorithm stops when the termination criterion is met.

In the first clustering model, researchers formed three clusters. The clustering process required 63 iterations to converge. The resulting clusters, including information on the number of students with dominant membership values in each cluster and their respective centroids, are presented in Table 3.

Table 3.
Result of First Clustering Model (3 Clusters)

Centroid **of Each Cluster**	**Number of Data**
$C_1 = (83.77,\ 79.48,\ 82.73)$	90
$C_2 = (73.07,\ 71.65,\ 69.21)$	119
$C_3 = (63.66,\ 64.82,\ 59.96)$	12

In the second clustering model, researchers formed four clusters. The clustering process required 86 iterations to converge. The resulting clusters, including information on the number of students with dominant membership values in each cluster and their respective centroids, are presented in Table 4.

Table 4.
Result of Second Clustering Model (4 Clusters)

Centroid **of Each Cluster**	**Number of Data**
$C_1 = (84.29,\ 80.66,\ 79.42)$	84
$C_2 = (71.79,\ 74.38,\ 69.03)$	65
$C_3 = (72.93,\ 69.67,\ 71.11)$	57
$C_4 = (64.08,\ 61.25,\ 59.06)$	15

In the final clustering model, researchers formed five clusters. The clustering process required 114 iterations to converge. The resulting clusters, including information on the number of students with dominant membership values in each cluster and their respective centroids, are presented in Table 5.

Table 5.
Result of Third Clustering Model (5 Clusters)

Centroid of Each Cluster	Number of Data
$C_1 = (82.62,\ 79.81,\ 80.44)$	49
$C_2 = (83.35,\ 80.29,\ 81.73)$	38
$C_3 = (73.19,\ 71.86,\ 70.09)$	60
$C_4 = (70.61,\ 68.54,\ 72.29)$	56
$C_5 = (61.85,\ 60.33,\ 64.01)$	18

After each cluster was formed, the clustering results were evaluated by identifying the silhouette coefficient value. The silhouette coefficient values for each clustering are presented in Table 6.

Table 6.
Silhouette Coefficient for Each Clustering Model

Number of Clusters	Silhouette Coefficient	Criteria
3 Clusters	0.6365	Medium Structure
4 Clusters	0.4064	Tensile Structure
5 Clusters	0.4112	Tensile Structure

Based on the silhouette coefficient values in the table above, the 3-cluster solution is the only one that falls into the medium structure category. Thus, researchers conclude that 3 clusters represent the optimal number for evaluating student academic performance. Referring to the institutions' academic regulations, the determination of grade scales with quality descriptions is elaborated in Table 7.

Table 7.
Grade Scale and Quality Description

Quality Symbol	Quality Description	Grade Scale
A	Exceptional	$x \geq 81$
A-	Excellent	$76 \leq x < 81$
B+	Above Good	$72 \leq x < 76$
B	Good	$68 \leq x < 72$
B-	Fair	$64 \leq x < 68$
C+	Above Sufficient	$60 \leq x < 64$
C	Sufficient	$56 \leq x < 60$
D	Poor	$41 \leq x < 56$
E	Fair	$x < 41$

Referring to Table 7, the first clustering model yielded three clusters with distinct characteristics. In the first cluster, centroid values ranged from 79.48 to 83.77, indicating that the 90 respondents in this cluster had an "excellent and exceptional" quality status. For the second cluster, centroid values were between 69.21 and 73.07, meaning the 119 respondents belonging to this cluster had a "good and above good" quality status. In the third cluster, centroid values ranged from 59.96 to 64.82, so the 12 respondents in this cluster were categorized as having a "sufficient, above sufficient, and fair" quality status.

The clustering results using the Fuzzy C-Means method offer a more flexible view of respondent membership to each cluster, as every student can possess a non-absolute degree of membership across multiple clusters. This approach more representatively illustrates the complexity of student academic data. Implementing Fuzzy C-Means clustering on academic data effectively groups students based on learning performance with good accuracy and provides recommendations for improving learning quality (Rosadi et al., 2017). Furthermore, fuzzy clustering methods can be employed to detect psychological aptitude and academic potential in students, which often remain hidden in multidimensional data (Han, 2023).

Moreover, utilizing this method in the context of higher education quality assurance can aid in designing more precise and adaptive data-driven policies. By examining the distribution of centroids and the proportion of student membership within each cluster, academic programs can target academic interventions more effectively (Jamhur, 2020). Fuzzy-based cluster analysis enhances accuracy in designing academic development programs, especially for students categorized in clusters with lower performance (Fadrial, 2020).

The evaluation results indicate that 12 students were assigned to the cluster with the smallest centroid values compared to other clusters. Additionally, this cluster showed that respondents had a "sufficient" to "fair" status. These evaluation findings serve as a recommendation for the academic institution to provide additional support and attention to students within this cluster. Furthermore, it is suggested that other students in clusters 1 and 2 maintain, and even improve, their academic performance in subsequent semesters.

The findings of this study also align with theories of mastery learning, particularly Bloom's Mastery Learning framework, which emphasizes that learners achieve competency at different rates depending on their prior knowledge and learning conditions (Zheng et al., 2020). The emergence of three distinct clusters (high, medium, and low performers) reflects the natural variation in students' mastery levels across core competencies in civil engineering (Saputra et al., 2022b). Students in the highest-performing cluster exhibit characteristics consistent with Bloom's assertion that mastery is attainable when adequate instructional support and feedback mechanisms are provided. Conversely, students in the lowest-performing cluster may require additional formative assessments, targeted instructional scaffolding, and structured remediation to achieve the same level of competency as their peers. This connection suggests that fuzzy clustering can serve as a diagnostic tool to identify mastery gaps and inform personalized instructional strategies (Charamba & Ndhlovana, 2025).

Finally, the distribution of students across the three clusters can also be interpreted through the lens of Tinto's Student Integration Theory (Castro-Montoya et al., 2025), which posits that academic success is strongly influenced by both academic and social integration within the educational environment. Students in the lower-performing cluster may experience weaker academic integration, limited engagement with learning communities, or insufficient interaction with instructors. This insight suggests that institutional policies aimed at strengthening mentorship, peer learning groups, and academic advising could significantly improve the performance of students in this cluster (Amalia et al., 2021b). By connecting fuzzy clustering outcomes with student integration theory, this study reinforces the importance of holistic academic support systems in higher education (Mohammad et al., 2025).

CONCLUSION

Based on the three clustering models that are being developed, the first clustering model with 3 cluster solution yielded the highest silhouette coefficient value, indicating it's the most robust model for evaluating student academic performance. Cluster 1, with a centroid of $(83.77, 79.48, 82.73)$ and 90 students, represents the highest-scoring group, reflecting excellent academic performance evaluations. Cluster 2, centered at $(73.07, 71.65, 69.21)$ with 119 students, signifies the second highest-scoring group, demonstrating good academic performance evaluations. Lastly, cluster 3, with a centroid of $(63.66, 64.82, 59.96)$ and comprising 12 students, represents the lowest-scoring group, indicating the most concerning academic performance evaluations.

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