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A Comparative Analysis of K-Means and Gaussian Mixture Models for Student Learning Behavior Clustering Using the Davies-Bouldin Index

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Abstract

Understanding student learning behavior remains a significant challenge in learning analytics, as accurate segmentation is essential for designing data-driven academic interventions. This study aims to compare the performance of two unsupervised clustering methods, K-Means and Gaussian Mixture Models (GMM), for grouping data on higher education students' learning behavior and to provide empirical evidence to support the selection of more appropriate segmentation methods. The study focuses on the capacity of both methods to produce compact, well-separated, and stable clusters using academic, behavioral, and social context attributes. The dataset underwent preprocessing, including handling missing data, encoding features, and standardizing to ensure consistent analysis. Evaluation was conducted through a series of experiments using the Davies–Bouldin Index as the primary cluster quality metric, accompanied by assessments of stability, variability, and consistency of clustering results across experiments. The most important finding is that K-Means produced more compact and well-separated clusters, with a lower average Davies–Bouldin value (2.04) than GMM (2.33), and exhibited higher stability. Conversely, GMM showed greater variability despite its ability to model overlapping clusters. These differences indicate that algorithm selection affects the quality and interpretability of segmentation. The findings confirm that K-Means is better suited to learning behavior data with a relatively linear structure. This study contributes to academic discourse on clustering algorithm selection and cluster validity evaluation in educational analytics, and offers methodological guidance for future research in higher education. Implications suggest that researchers and practitioners should consider data-structure characteristics and validity metrics before using segmentation results to design targeted, data-driven academic interventions, thereby avoiding misinterpretation.

Keywords: *Davies–Bouldin Index, Gaussian Mixture Models, K-Means Clustering, Student Learning, Unsupervised Learning*

A. Introduction

The analysis of student learning behavior has become a major focus in higher education research, in line with the growing need for institutions to implement data-driven academic decision-making (Dina, Saona, & Paz; Anggraini, Korespondensi, & Mesin). Learning analytics approaches leverage educational data to uncover patterns of student behavior related to learning engagement, study habits, and socio-academic factors that influence academic achievement (Dewi Anggraini, Korespondensi, & Mesin, 2025; Sunarya, Asri, Azizah, & Lim, 2025). Within this context, unsupervised learning techniques—particularly clustering play a crucial role in identifying latent student profiles without prior labels, thereby enabling the design of more adaptive and personalized learning interventions.

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Among various clustering methods, K-Means and Gaussian Mixture Models (GMM) are two of the most widely used algorithms due to their conceptual simplicity and effectiveness across diverse application domains. K-Means is well known for its strong performance on data with linear structures and relatively well-separated clusters, whereas GMM provides a probabilistic framework that models more complex data distributions using mixtures of Gaussian components (Totti & Setiyawati, 2025). These characteristics have led to the extensive adoption of both algorithms in fields such as image processing, bioinformatics, and recommender systems. However, within the domains of educational data mining and learning analytics, empirical studies that systematically compare K-Means and GMM—particularly using heterogeneous student learning behavior data—remain relatively limited.

Most prior studies in educational contexts tend to focus on a single clustering algorithm or rely predominantly on online activity data derived from Learning Management Systems (LMS), such as access frequency or clickstream data (Javadikasgari et al., 2018; Zhang, Ghandour, & Shestak, 2020). While such data provide valuable insights into student engagement in digital learning environments, they often fail to comprehensively represent students' overall learning behaviors. Important aspects such as out-of-class study habits, sleep patterns, attendance, socio-economic background, and participation in non-academic activities are frequently overlooked, resulting in cluster profiles that are insufficiently holistic.

Beyond limitations in data scope, a research gap is also evident in the strategies used to evaluate clustering quality. Previous studies have commonly employed metrics such as the Silhouette Score or the Calinski–Harabasz Index, whereas the Davies–Bouldin Index (DBI), which explicitly measures the balance between intra-cluster compactness and inter-cluster separation, has been relatively underutilized in analyses of student learning behavior (Farida & Lubis, 2025; Xiao, Lu, & Li, 2017). In fact, DBI is highly sensitive to the quality of cluster structures, particularly for behavioral data that often exhibit overlapping patterns and non-uniform distributions. Therefore, the limited use of DBI-based evaluation within learning analytics indicates a significant empirical gap.

Although K-Means and GMM have been widely applied in unsupervised learning research, to date there remain few studies that explicitly (1) compare the performance of these two algorithms using heterogeneous student learning behavior data, and (2) evaluate clustering stability and quality by positioning the Davies–Bouldin Index as the primary evaluation criterion. The absence of such comparative analyses limits methodological guidance for researchers and practitioners in selecting the most appropriate clustering algorithms for complex, multidimensional educational data.

Accordingly, this study aims to address these gaps by conducting a comparative analysis of K-Means and Gaussian Mixture Models on a student learning behavior dataset encompassing academic, behavioral, and socio-contextual variables, including study duration, sleep patterns, attendance, assignment completion, class participation, internet access, parental education level, and involvement in non-academic activities. By emphasizing DBI-based evaluation across multiple experimental scenarios, this research is expected to contribute both methodologically and empirically to the application of unsupervised learning in educational analytics.

Clustering is a fundamental technique in unsupervised learning that groups data into homogeneous clusters based on the degree of similarity among their characteristics (Rodriguez et al., 2019; Sinaga & Yang, 2020). In educational research, clustering has been widely employed to understand patterns of student learning behavior, identify learner profiles, and support decision-making in the contexts of learning analytics and personalized learning (Palani, Stynes, & Pathak, 2021; Swetha, Thaila Shree, Soundaravalli, & Lincy, 2025). A number of previous studies have demonstrated that clustering methods are effective in grouping students

according to levels of participation, study habits, academic performance, and interactions with digital learning platforms (Priyaadharshini, NathaMayil, Dakshina, Sandhya, & Bettina Shirley, 2020), in addition to other approaches such as Hierarchical Clustering and Self-Organizing Maps (SOM). K-Means is one of the most popular clustering algorithms due to its computational efficiency and its ability to handle large-scale datasets (Syakur, Khotimah, Rochman, & Satoto, 2018). By minimizing the distance between data points and cluster centroids, K-Means performs optimally when clusters are spherical and have relatively balanced variance. In the context of educational data, several studies have reported that K-Means produces stable and easily interpretable clusters, particularly when learning-related features exhibit a clear geometric structure. Nevertheless, K-Means has notable limitations, including sensitivity to outliers, dependence on centroid initialization, and the assumption of uniform cluster shapes and variances, which may degrade its performance on data with complex or overlapping distributional patterns (Sinaga & Yang, 2020). In contrast, Gaussian Mixture Models (GMM) adopt a probabilistic approach to clustering by modeling data as a combination of multiple Gaussian distributions (Totti & Setiyawati, 2025; Weber, Ray, Valverde, Clark, & Sharma, 2022). Unlike K-Means, which relies on hard cluster assignments, GMM provides probabilistic estimates of data point membership across clusters, offering greater flexibility in modeling non-linear and overlapping cluster structures (Yang, Lai, & Lin, 2012). The literature suggests that GMM can outperform K-Means when dealing with data characterized by heterogeneous variance across dimensions or non-symmetric cluster shapes. However, GMM also presents challenges, including higher computational complexity and sensitivity to covariance estimation, particularly in educational datasets of moderate size.

Cluster quality evaluation is a critical aspect of clustering research. The Davies–Bouldin Index (DBI) is an internal validation metric commonly used to assess clustering quality, based on the ratio of intra-cluster similarity to inter-cluster separation, where lower values indicate better-defined cluster structures. Although DBI has been applied in various clustering studies, its use in analyzing student learning behavior remains relatively limited compared to other metrics. Comparative studies between K-Means and GMM have predominantly been conducted on general-purpose datasets, leaving the specific context of student learning behavior characterized by complex academic and socio-contextual attributes largely underexplored. Overall, the literature review indicates that K-Means and GMM each have distinct strengths and limitations, and their effectiveness depends heavily on the dataset's characteristics. However, the scarcity of comparative studies that emphasize DBI-based evaluation within educational contexts underscores the need for further research in this area.

B. Methods

The research methodology was designed following the Knowledge Discovery in Databases (KDD) framework, which consists of the stages of data collection, data preprocessing, data transformation and feature engineering, clustering algorithm implementation, and cluster quality evaluation. All analytical procedures were conducted in Python, using the scikit-learn library to ensure experimental consistency and reproducibility. Conceptually, the research workflow can be represented as a KDD flow diagram comprising the following stages: (1) data selection, (2) data preprocessing, (3) data transformation and feature engineering, (4) clustering, and (5) cluster evaluation.

Dataset and Data Source

The dataset used in this study was obtained from Kaggle, specifically the *student learning behavior dataset*. This dataset comprises academic, behavioral, and socio-contextual variables,

including weekly study hours, daily sleep duration, attendance percentage, assignment completion, class participation level, internet access, parental education level, involvement in extracurricular activities, and part-time employment status. The selection of a Kaggle dataset was based on several considerations. First, the dataset is publicly available and well-documented, allowing other scholars to replicate and verify research findings. Second, the included variables represent diverse dimensions of student learning behavior, extending beyond online activity data and thereby offering a more holistic representation of student learning patterns. Third, the dataset has undergone anonymization, ensuring that no personally identifiable information is included and that ethical considerations regarding secondary data use in educational research are met.

Nevertheless, the use of secondary data entails certain limitations, particularly regarding potential bias. The dataset may not fully represent the global student population due to variations in institutional contexts, learning cultures, and educational systems. Consequently, the findings of this study are interpreted as empirical results that are specific to the characteristics of the dataset employed.

Data Preprocessing

The data preprocessing stage was conducted to ensure that the dataset was suitable for clustering analysis. The initial dataset contained both quantitative variables (e.g., weekly study hours, daily sleep duration, attendance rate, and assignment scores) and categorical variables (e.g., participation level, internet access, parental education level, and extracurricular activities). Data preprocessing was performed through the following steps:

Handling Missing Values

Missing values were addressed using statistical imputation techniques. For numerical variables, missing values were replaced with either the mean or median, depending on the data distribution. For categorical variables, imputation was performed using the mode. This approach was selected to preserve the dataset size while minimizing the introduction of extreme bias.

$$x_i' = \frac{1}{n}\sum_{j=1}^{n} x_{ij} \qquad (1)$$

Categorical Variables

Categorical variables, including participation level, internet access, and parental education level, were converted into numerical features using one-hot encoding. This transformation was necessary to ensure that all variables could be processed consistently by both the K-Means and Gaussian Mixture Model algorithms.

Data Normalization

All numerical features were standardized using StandardScaler, so that each feature had a mean of 0 and a standard deviation of 1. The standardization process is defined as:

$$zi\,\frac{x_i-\mu}{\sigma} \qquad (2)$$

Here x_i denotes the value of the i-th feature, μrepresents the mean, and σdenotes the standard deviation. This standardization step is crucial because K-Means is sensitive to feature scaling, while GMM relies on accurate covariance estimation.

Feature Engineering

In addition to the original features, this study applies feature engineering to enrich the representation of student learning behavior. Several derived features were constructed, including:

a. Daily study ratio, representing learning intensity relative to available daily time.
b. Digital learning resource usage intensity, aggregating indicators of internet access and participation in technology-based learning activities.
c. Learning consistency score, combining attendance and assignment completion metrics.

Feature engineering aims to capture learning behavior patterns that may not be directly reflected in raw features. By integrating multiple indicators into composite variables, the derived features are expected to enhance cluster separability and improve clustering quality, as evaluated using the Elbow method.

$$WCSS(k) = \sum_{i=1}^{k} \sum_{x \in C_i} |x - \mu_i|^2 \quad (3)$$

And also Silhouette

$$s(i) = \frac{b(i) - a(i)}{\max(a(i), b(i))} \quad (4)$$

Clustering Algorithms

K-Means Clustering

K-Means is an unsupervised clustering algorithm that aims to minimize the sum of squared distances between data points and their corresponding cluster centroids. The objective function of K-Means can be expressed as:

$$J = \sum_{i=1}^{k} \sum_{x_j \in C_i} \|x_j - \mu_i\|^2 \quad (5)$$

Where $k$denotes the number of clusters, $C_i$represents the i-th cluster, and $\mu_i$denotes the centroid of the i-th cluster. Centroid initialization was performed using the k-means++ method to improve clustering stability and accelerate convergence. The iterative process was terminated when the change in centroid positions fell below a predefined threshold or when the maximum number of iterations was reached.

Gaussian Mixture Model (GMM)

The Gaussian Mixture Model (GMM) represents data as a combination of multiple multivariate Gaussian distributions. The probability density function of a GMM is defined as:

$$p(x) = \sum_{k=1}^{K} \pi_k \mathcal{N}(x \mid \mu_k, \Sigma_k) \quad (6)$$

Where $\pi_k$denotes the mixing weight of the k-th component, $\mu_k$is the mean vector, and $\Sigma_k$represents the covariance matrix of the k-th cluster. Parameter estimation was performed using the Expectation–Maximization (EM) algorithm, iterating until convergence based on changes in the log-likelihood value.

Determination of the Number of Clusters

The optimal number of clusters was determined using a combination of the Elbow Method, Silhouette Score, and the Davies–Bouldin Index (DBI). This multi-metric approach was adopted to avoid reliance on a single criterion and to enhance the structural validity of the clustering results.

Cluster Evaluation Using the Davies–Bouldin Index

The Davies–Bouldin Index (DBI) was employed as the primary evaluation metric because it balances intra-cluster compactness and inter-cluster separation. The DBI is defined as:

$$DBI = \frac{1}{k}\sum_{i=1}^{k}\max_{j\neq i}\left(\frac{S_i + S_j}{M_{ij}}\right) \tag{7}$$

Where $S_i$denotes the average intra-cluster distance of the i-th cluster, and M_{ij}represents the distance between the centroids of clusters $i$and j. DBI was selected because it is particularly well suited for heterogeneous educational data, which often exhibit overlapping cluster structures. Lower DBI values indicate better and more stable clustering configurations. To assess the consistency of the results, DBI evaluation was conducted across multiple experiments with different initialization settings.

C. Results and Discussion

Descriptive Data Analysis

Descriptive analysis was conducted to provide an initial overview of the characteristics of the student learning behavior data prior to clustering. Descriptive statistics for the main quantitative variables are presented in **Table 1**.

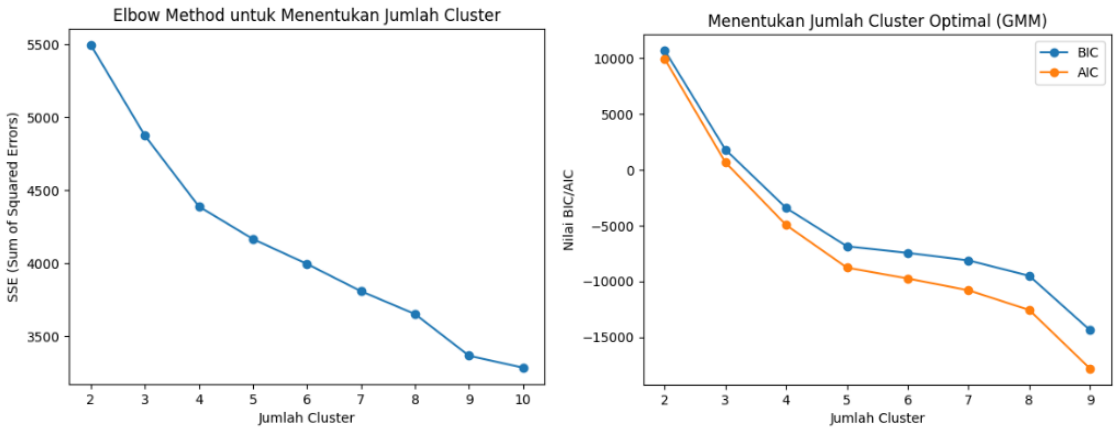
Table 1. Descriptive Statistics

Variabel	Mean	Std	Min	Max
study_hours_per_week	0.50	0.23	0.05	0.98
sleep_hours_per_day	0.50	0.29	0.01	0.99
attendance_percentage	0.70	0.19	0.32	1.00
assignments_completed	0.57	0.29	0	1
final_grade	69	14	33	98

Based on Table 1, the variables of study hours and sleep duration show a relatively even distribution, with moderate standard deviations. The attendance percentage has a high average value (0.70), while the final grade shows considerable variation, ranging from 33 to 98. This variation indicates heterogeneity in behavior and academic achievement that is relevant to the clustering process.

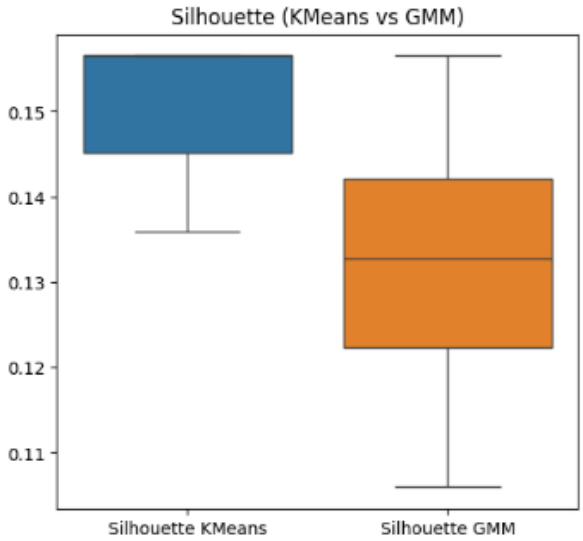
Determination of the Number of Clusters

The optimal number of clusters was determined using the Elbow Method and Silhouette Score for both the K-Means and Gaussian Mixture Model algorithms. The results of the Elbow Method are illustrated in Figure 1, which indicates an elbow point at four clusters.



Graph 1. Determination of the optimal number of clusters

The evaluation based on the Silhouette Score is presented in Figure 2. The Silhouette values for K-Means range from 0.145 to 0.155, whereas GMM exhibits lower and more variable Silhouette scores. Based on the combination of these two methods, the number of clusters was set to 4 for both algorithms to maintain consistency in the comparative analysis.



Graph 2. Silhouette Score values

Clustering Results Using K-Means

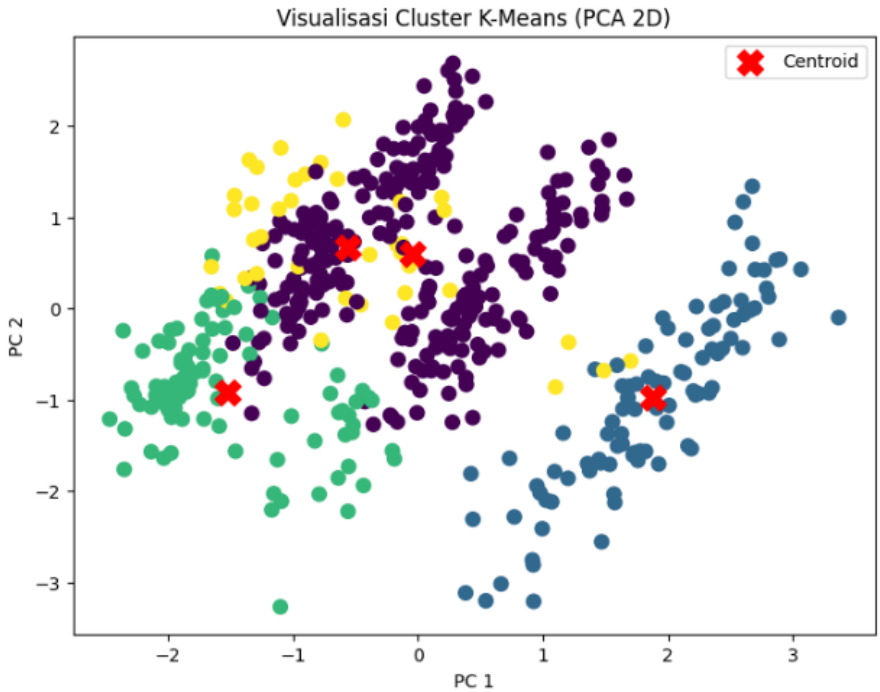
The K-Means clustering results yielded four clusters with standardized centroid values. The mean feature values for each cluster are presented in Table 2.

Table 2. K-Means clustering results

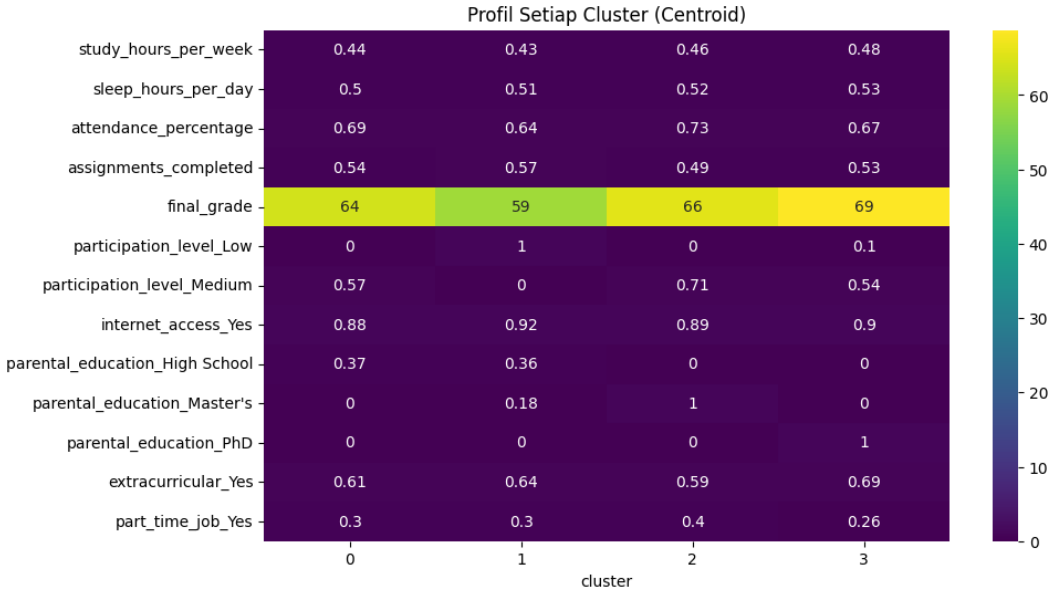
Variabel	Cluster 0	Cluster 1	Cluster 2	Cluster 3
study_hours_per_week	-0.0279	-0.0775	0.0678	0.2155
sleep_hours_per_day	-0.0372	0.0031	0.0458	0.1328
attendance_percentage	0.0155	-0.2260	0.2024	-0.0472
assignments_completed	0.0119	0.1213	-0.1486	-0.0132
participation_level_Low	-0.5031	1.9876	-0.5031	-0.2477
participation_level_Medium	0.1707	-0.9685	0.4549	0.1090
internet_access_Yes	-0.0315	0.0880	-0.0109	0.0238

Variabel	Cluster 0	Cluster 1	Cluster 2	Cluster 3
parental_education_High School	0.2321	0.2096	-0.6051	-0.6051
parental_education_Master's	-0.5434	-0.1257	1.8401	-0.5434
parental_education_PhD	-0.2909	-0.2909	-0.2909	3.4381
extracurricular_Yes	-0.0155	0.0436	-0.0625	0.1529
part_time_job_Yes	-0.0352	-0.0366	0.1851	-0.1282
Cluster_GMM	1.8802	0.0000	3.0000	0.8974

For example, Cluster 2 has an attendance Z-score of 0.2024, indicating an above-average attendance rate, while Cluster 1 has a low participation Z-score of 1.9876, the highest among all clusters. The visualization of the K-Means clustering results in two-dimensional space using PCA is shown in Graph 3, while the distribution of centroid values is visualized using a heatmap in Graph 4.



Graph 3. K-Means cluster visualization



Graph 4. Heatmap K-Means

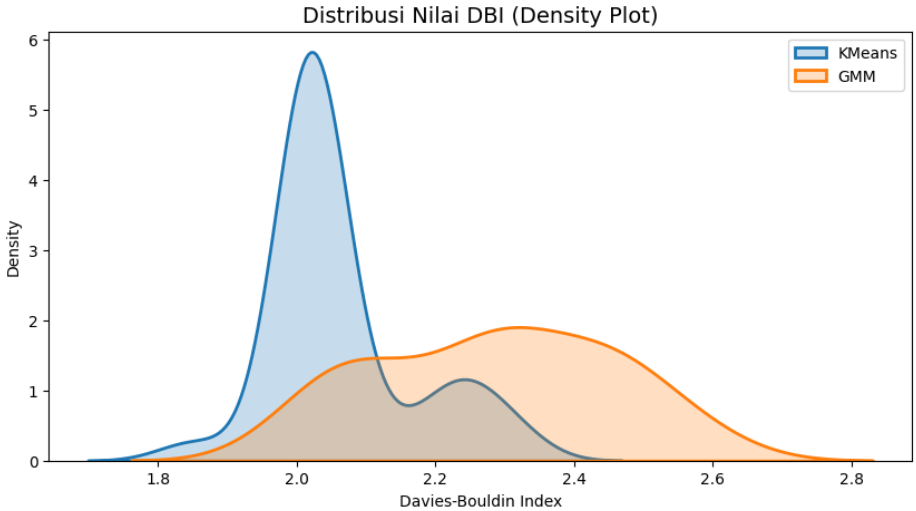
Cluster Quality Evaluation

Cluster quality evaluation was conducted using the Davies–Bouldin Index (DBI) as the primary metric. A summary of the DBI values for K-Means and GMM is presented in Table 4.

Table 4. Davies–Bouldin Index (DBI) Statistics

Statistik	DBI KMeans	DBI GMM
Count	30.000000	30.000000
Mean	**2.042443**	**2.331236**
Std	0.082940	0.187233
Min	1.852576	2.019157
25%	2.019157	2.249425
50% (Median)	2.019157	2.319503
75%	2.019157	2.455304
Max	2.299248	2.819221
Model	Rata-rata DBI	
KMeans	2.0424433017	
GMM	2.3312364865	

Based on Table 4, K-Means yields an average DBI of 2.04, lower than GMM's 2.33. In addition, the standard deviation of the K-Means DBI (0.08) is smaller than that of GMM (0.18), indicating lower variation in cluster quality between experiments. The distribution of DBI values is shown in Figure 7, while the variation in DBI values per experiment is shown in Figure 8.



Graph 7. Distribution of DBI Values

D. Conclusion

The findings of this study provide empirical insights into the performance differences between the K-Means and Gaussian Mixture Model (GMM) algorithms in clustering student learning behavior. Based on quantitative evaluation using the Davies–Bouldin Index (DBI), K-Means consistently produced more compact and better-separated cluster structures than GMM. These results not only highlight differences in algorithmic performance but also reflect the latent characteristics of the analyzed student learning behavior data.

From a theoretical perspective, the superior performance of K-Means in this study can be attributed to the geometric assumptions underlying the algorithm. K-Means optimizes Euclidean distance to cluster centroids and therefore performs optimally on data with relatively linear cluster structures and homogeneous variance. Cluster visualizations in the PCA space, as illustrated in Figures 3 and 5, indicate that most clusters are relatively compact with clearly defined boundaries, supporting the suitability of K-Means for the dataset's characteristics. In contrast, GMM assumes multivariate Gaussian distributions and estimates full covariance matrices, which—when applied to datasets with limited dimensionality and sample size may result in more overlapping and less stable cluster formations.

These findings are consistent with prior studies reporting that K-Means tends to outperform probabilistic approaches on educational datasets characterized by relatively simple feature structures and moderate inter-variable correlations (Syakur et al., 2018). Conversely, other studies have demonstrated that GMM performs better on datasets exhibiting non-linear patterns and high dimensionality-wise variance (Totti & Setiyawati, 2025; Yang et al., 2012). Such discrepancies suggest that no single clustering algorithm is universally optimal; instead, performance depends heavily on dataset characteristics, including feature distributions, variable scaling, and the degree of overlap between clusters.

One notable finding of this study concerns clustering stability. The lower standard deviation of DBI values observed for K-Means compared to GMM indicates that K-Means produces more consistent cluster structures across different initialization settings. This aspect is particularly relevant in the context of learning analytics, where cluster stability is crucial to ensure that student segmentation does not fluctuate substantially due to technical variations, thereby supporting reliable long-term academic decision-making.

From an educational perspective, the clustering results have significant practical implications. Segmenting students based on learning behavior enables educational institutions to identify groups with specific learning characteristics, such as high attendance but low participation, or high learning intensity coupled with suboptimal time management. Such insights can be leveraged to design more adaptive learning interventions, including academic mentoring programs, differentiated instructional strategies, and early warning systems for detecting academic risk. In this sense, clustering outcomes function not merely as analytical results but as a foundation for informed policy-making and targeted instructional strategies.

The primary methodological contribution of this study is the use of the Davies–Bouldin Index as the primary evaluation metric for student learning behavior data. While most previous studies have relied predominantly on the Silhouette Score or the Calinski–Harabasz Index [5][6], this study demonstrates that DBI provides a more sensitive evaluation of the balance between intra-cluster compactness and inter-cluster separation in heterogeneous educational datasets. This finding enriches the clustering validation literature by emphasizing that the choice of evaluation metric is as critical as the choice of clustering algorithm itself.

Despite its empirical and methodological contributions, this study has several limitations that should be acknowledged. The dataset used is secondary data from a specific institutional context; therefore, the generalizability of the findings should be interpreted with caution. Moreover, this study focused on two primary clustering algorithms; future research could explore alternative approaches, such as density-based clustering or deep clustering methods, to gain additional insights. These limitations point to promising directions for further research aimed at expanding both the analytical approaches and application contexts.

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