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CLUSTERING SENIOR HIGH SCHOOL STUDENTS' NUMERACY SCORE IN JAVA USING THE K-MEANS ALGORITHM

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Abstract
Numeracy skill is a key ability that supports critical thinking and is assessed in Indonesia through the Minimum Competency Assessment. This study aims to (1) analyze high school students' numeracy skills in Java based on four numeracy domains and three cognitive levels; and (2) cluster students' numeracy skills using the K-Means algorithm with the Davies-Bouldin Index (DBI) as the evaluation metric. The data were obtained from the education data portal for the year 2021–2023. The process went through several stages: data cleaning, normalization, feature selection, clustering, and validation using the Davies–Bouldin Index (DBI). The results indicate a steady improvement in students' numeracy performance, with average scores increasing from 51.18 in 2021, 54.08 in 2022, and 59.19 in 2023. The clustering process resulted in four clusters in 2021 and 2022 and two clusters in 2023. The clustering results revealed four distinct groups in 2021 and 2022, representing high, moderate, fluctuating, and low numeracy performance across regions. In 2023, these merged into two clusters, indicating reduced disparity and greater uniformity in students' numeracy achievement across Java. Furthermore, it provides insights for educators and policymakers to design targeted interventions to improve students' numeracy skills and reduce learning gaps across regions.

Keywords: clustering, Davies-Bouldin Index, K-Means algorithm, national assessment, numeracy

Introduction

Numeracy is a crucial skill for every individual. In the 21st century, where technological advancements and digitalization are so prevalent, this ability is crucial for supporting critical thinking skills, enabling better decision-making, and contributing to individual well-being (Fajriyah, 2022; Nurfadillah et al., 2024). Numeracy itself can be defined as the ability to use basic mathematics, such as numbers and symbols, to solve real-world problems and analyze information presented in graphs, tables, and other forms (Mariamah et al., 2021). This demonstrates that numeracy is not limited to academic contexts but also contributes significantly to everyday life.

In Indonesia, numeracy is one of the cognitive abilities measured through the Minimum Competency Assessment (AKM) in the National Assessment (Kementerian Pendidikan, Kebudayaan, Riset, dan Teknologi Republik Indonesia, 2021). This assessment is designed to measure students' competency levels, which can be used to design improvements to the learning process and improve student learning outcomes. There are four numeracy competency domains used in the AKM: Number, Geometry and Measurement, Algebra, and Data and Uncertainty. Numeracy is measured across three cognitive levels: Knowing, Applying, and Reasoning.

The results of the 2021-2023 National Assessment (AN) for high school students indicate that student competency achievement is still suboptimal and tends to vary. This aligns with the statement by Sukaryo and Sari (2024), who stated that the numeracy skills of high school students in Indonesia are still suboptimal and need to be improved. Yet, improving numeracy skills is a crucial factor in developing high-quality and competitive human resources (Anderha & Maskar, 2021). This situation certainly poses a challenge for Indonesia in improving and equitable education, including in numeracy.

With the advancement of technology, educational data, such as National Assessment results, can be further processed and analyzed to help address various challenges in education. One possible approach is data mining, which is the process of extracting valuable knowledge from data using mathematical, statistical, and artificial intelligence techniques (Kononeko & Kukar, in Muttaqin et al., 2023). Data mining can facilitate data collection, processing, and analysis to support better decision-making in education.

The data mining method used in this study is clustering with the K-Means algorithm. Clustering is a method of grouping objects based on certain conditions, where objects within a group (cluster) have a high degree of similarity to each other and a high degree of dissimilarity to objects in other clusters (Farissa et al., 2021). With this method, national assessment results are used to group regions with similar numeracy ability characteristics, thus enabling them to develop more targeted learning improvement strategies.

The K-Means clustering algorithm is one of the oldest, most powerful, and most popular data mining techniques used in research because of its ease of implementation and high processing speed (Ahmed et al., 2020; Faizah et al., 2020). It has a high level of accuracy regarding object size, allowing it to efficiently handle large datasets (Rosida & Wijaya, 2023). The K-Means algorithm has been widely used in educational research, such as clustering national exam results (Suputra et al., 2021), grouping high-achieving students (Rahayu et al., 2024), and identifying scholarship recipients (Harahap & Rambe, 2021).

However, the quality of K-Means clustering results is highly dependent on the initial selection of cluster centers, so it is very important to determine the initial cluster centers correctly (Yu et al., in Setyaningtyas et al., 2022). One method that can be used to evaluate clustering results is the Davies-Bouldin Index (DBI). The results of the DBI calculation can be used as a reference in determining the optimal number of clusters, which is achieved when the model produces the smallest DBI value (Ashari et al., 2022).

This research focuses on the island of Java, which is the center of economic, political, and other development activities in Indonesia. Java also dominates Indonesia's population, accounting for 56.1% (Purnamasari, 2024). Furthermore, as a major center of education, Java plays a crucial role in the advancement of education in Indonesia, particularly with its easy access, comprehensive facilities, and high standards (Putri et al., 2023).

Based on this background, this study focuses on Java Island as a region with a strategic role in educational development in Indonesia. Java Island has a relatively advanced educational infrastructure and the largest population, but still shows variations in numeracy achievement between provinces. Therefore, this study aims to (1) analyze the numeracy abilities of senior high school students in Java Island based on four numeracy domains and three cognitive levels, and (2) group students' numeracy abilities using the K-Means algorithm with the Davies–Bouldin Index (DBI) as an evaluation metric.

Method

This study uses secondary data in the form of national assessment results taken from the education data portal at https://data.kemendikdasmen.go.id/. The data used are high school students' numeracy scores from the 2021-2023 National Assessment, covering the following variables.

Table 1. Description of Research Variables

Variable	Description
kd_siswa_an	Student code
kd-kokab	City/regency code
provinsi	Province
NUM	Numeracy score
NUM_ALJ	Score in Algebra domain
NUM_GEO	Score in Geometry domain
NUM_BIL	Score in Number domain
NUM_DAT	Score in Data and Uncertainty domain
NUM_L1	Score in level 1 (Knowing)
NUM_L2	Score in level 2 (Applying)
NUM_L3	Score in level 3 (Reasoning)

This research focuses on the island of Java, which includes the provinces of Banten, Jakarta, West Java, Central Java, Yogyakarta, and East Java. Data were collected for 10,141 cases in 2021, 10,264 cases in 2022, and 10,266 cases in 2023. Of the 119 regencies/cities in Java, available data only cover 82. Data processing was performed using Python.

Table 2. Distribution of Students and Schools by Province in Java

	Number of Students			Number of Schools		
Province	2021	2022	2023	2021	2022	2023
Banten	1979	2009	2035	57	56	56
West Java	1773	1765	1828	48	47	47
DKI Jakarta	1222	1291	1282	35	34	34
Central Java	1505	1545	1566	40	40	40
DIY	1471	1518	1514	42	41	41
East Jawa	2040	2004	1963	59	57	58

Data analysis in this study was conducted through five main stages: (1) data cleaning, (2) standardization, (3) feature selection, (4) clustering, and (5) validation. These stages were adapted from the general procedure for data mining analysis using the K-Means algorithm (Stiadi & Sundani, 2021).

1. Data Cleaning

At this stage, data cleaning was performed, including handling missing values, duplicate data, and outliers. Missing values were removed without input to maintain the authenticity of the data used in the analysis. Meanwhile, no duplicate data was found in 2021, 2022, or 2023. However, outliers were not removed because they could provide important insights into the actual situation. After data cleaning, clean data were obtained for 9.990 in 2021, 10.132 in 2022, and 10.188 in 2023. The number of participating students and schools is presented in Table 2.

2. Standardization

At this stage, data standardization is carried out on the 'NUM' variable, which will be used as a reference for the clustering process.

3. Feature Selection

In the feature selection stage, variables used in the clustering process are selected based on their relevance to students' numeracy abilities. The variables used include numeracy domain scores (NUM, NUM_ALJ, NUM_GEO, NUM_BIL, NUM_DAT) and cognitive levels (NUM_L1, NUM_L2, NUM_L3). This feature selection aims to obtain the most informative data representation and avoid redundancy between variables.

4. Clustering

The clustering process is performed using the K-Means algorithm. This algorithm works by minimizing the sum of the distances in each cluster using the Euclidean distance measure, performed iteratively (Aditya et al., 2020). The steps in this algorithm are as follows (Maori & Evanita, 2023).

1) Determine the number of clusters (k value) to be formed.
2) Randomly determine the initial center points (k centroids) for each cluster.
3) Calculate the distance between each data point and each centroid using the following formula for the distance between two objects (Euclidean distance).

$$D_{ij} = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2 + \cdots \left(n_i - n_j\right)^2}$$

with:
D_{ij} = distance between objects i dan centroid j
x_i = x coordinate of the object
x_j = x coordinate of center (centroid)
y_i = y coordinate of the object
y_j = y coordinate of center (centroid)

4) Group the data into clusters based on the closest distance between the data and the centroid.
5) Determine the new centroid by calculating the average value of all data in each cluster.
6) Repeat steps 3-5 until you find a suitable cluster that meets certain conditions.

5. *Validation*

The best number of clusters (k value) is determined based on the Davies-Bouldin Index (DBI) calculation. DBI evaluates clusters based on the proximity between cluster members (intra-cluster distance) and the separation between clusters (inter-cluster distance). The DBI calculation can be performed using the following formula (Hassan et al., 2021),

$$DBI = \frac{1}{k}\sum\nolimits_{i=1}^{k} \max_{i \neq j} R_{i,j}$$

where

$$R_{i,j} = \frac{WSS_i + WSS_j}{BSS_{i,j}}$$

$$WSS_i = \frac{1}{n_i}\sum\nolimits_{i=1}^{n_i} d(x_i - c_i)$$

$$BSS_{i,j} = d\left(c_i, c_j\right)$$

where $d(x, y)$ is the distance between two points, WSS_i is the average intra-cluster distance between data (x_i) and the centroid (c_i) of the cluster, $BSS_{i,j}$ is the inter-cluster distance between the centroids of cluster i (c_i) and cluster j (c_j), and $R_{i,j}$ is the ratio between the inter-cluster and intra-cluster distances. The best k value is determined from the smallest DBI value, namely by striving for maximum inter-cluster distance and minimum intra-cluster distance (Jollyta et al., 2023). A large inter-cluster value indicates bigger differences between clusters, or in other words, smaller similarities between clusters, while a small intra-cluster value indicates better similarities within a cluster (Gustriansyah et al., 2020).

Findings and Discussion

Descriptive Analysis

Based on Table 3 and Figure 1, it can be seen that there is an increase in high school students' numeracy scores from year to year. In 2021, the average numeracy score was recorded at 51.18, then increased to 54.08 in 2022 and reached 59.19 in 2023.

Table 3. Average Numeracy Score of Senior High School Students in Java Based on Domains and Cognitive Levels (2021-2023)

Observed Aspects	2021	2022	2023
Numeracy	51.18	54.08	59.19
Aljabar Domain	49.89	53.50	59.14
Geometry Domain	49.66	53.09	57.34
Number Domain	51.38	52.75	58.55
Data and Uncertainty Domain	51.54	52.27	60.44

Knowing	49.79	52.73	54.39
Applying	51.00	55.13	59.57
Reasoning	51.94	52.45	58.54

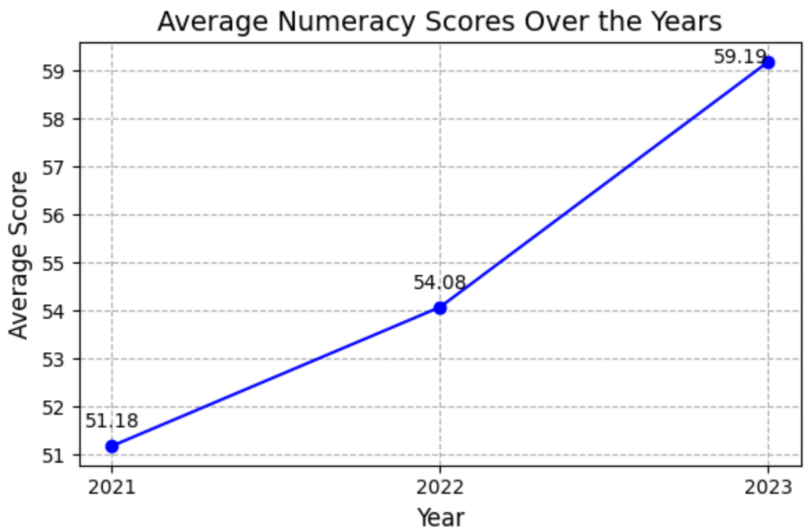

Figure 1. Average Numeracy Scores Over the Years

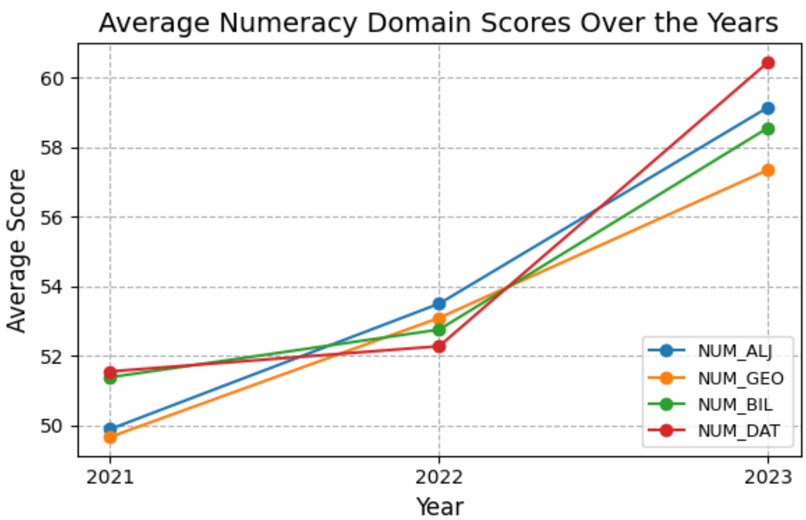

Figure 2. Average Numeracy Domain Scores Over the Years

Based on the numeracy domain, as shown in Figure 2, it can be seen that all domains have increased each year. The most significant improvement occurred in the Data and Uncertainty domain, followed by the Algebra domain, indicating growing student abilities in interpreting data, understanding probability, and performing symbolic reasoning. The results of this study are in line with the findings of Nugraha and Rudhito (2025), who also noted a significant increase in the Data and Uncertainty domain.

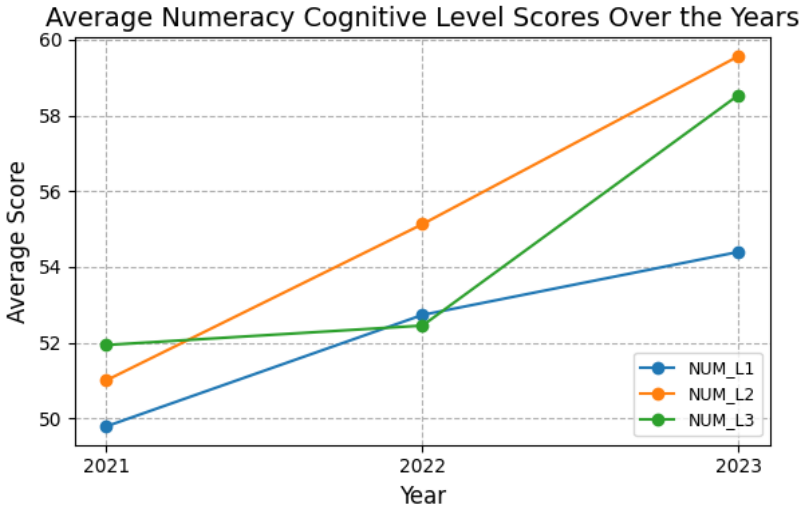

Figure 3. Average Numeracy Cognitive Level Scores Over the Years

Based on cognitive levels, as shown in Figure 3, the applying competency (L2) experienced fairly steady improvement and became the highest competency in 2022 and 2023. The reasoning competency (L3) showed the most significant improvement in 2023, compared to other competencies. Meanwhile, the knowing competency (L1), the most basic competency, tended to be the lowest-performing, although it also experienced improvement from year to year. This may indicate a lack of students' fundamental understanding of basic numeracy concepts. However, it also indicates that the learning process in schools is beginning to emphasize higher-order thinking skills (HOTS), rather than simply procedural and memorizing material. This is a positive sign because it indicates an improvement in the quality of students' thinking abilities.

The three graphs in Figures 4-6 show variations in average numeracy scores across regencies/cities on Java Island during the 2021-2023 period. The dashed red line in each graph represents the average numeracy score for Java Island. It can be seen that the majority of regions have average scores close to the overall average for Java Island. However, several regions remain extremely prominent, either significantly above or significantly below the average. This situation illustrates the persistence of gaps in numeracy learning between regions.

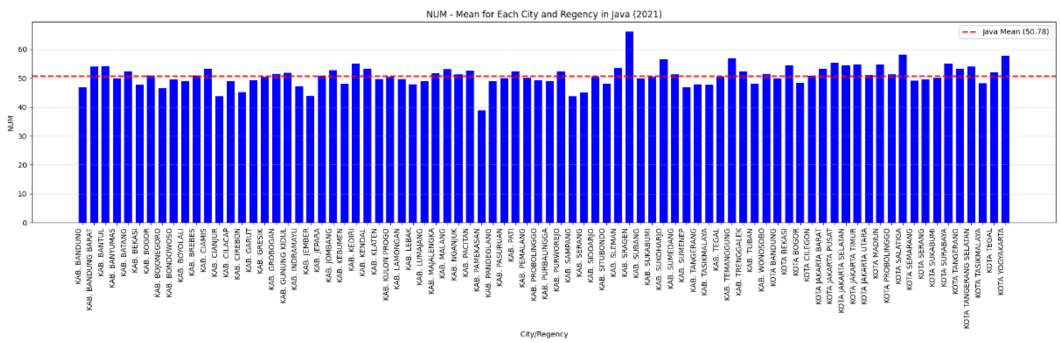

Figure 4. Average NUM Score for Each City and Regency in Java (2021)

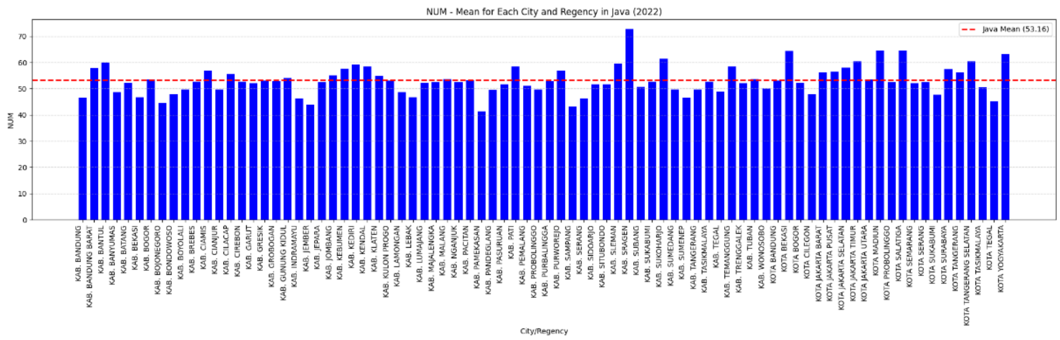

Figure 5. Average NUM Score for Each City and Regency in Java (2022)

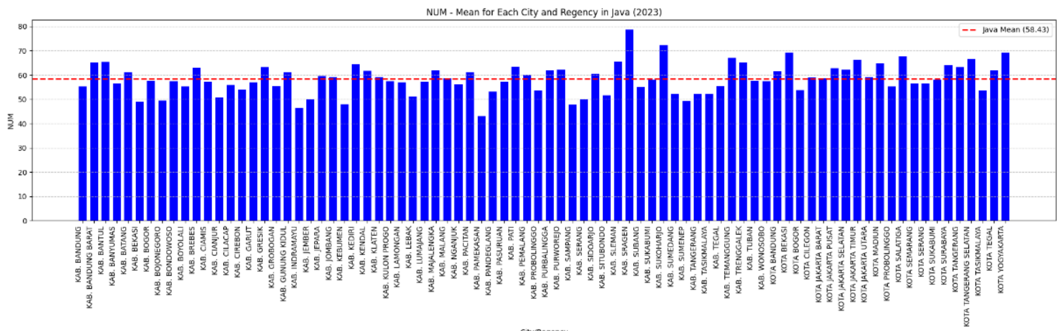

Figure 6. Average NUM Score for Each City and Regency in Java (2023)

The data shows that Sragen Regency consistently ranks among the regions with the highest average numeracy scores in Java. When viewed provincially, as shown in Table 4, DKI Jakarta and Yogyakarta consistently achieve higher average numeracy scores than other provinces on Java, while Banten consistently ranks last. Overall, there is a trend of increasing numeracy skills across all provinces, indicating an improvement in the quality of learning from year to year. However, the gap in numeracy scores has also widened each year, from 4.52 points in 2021 to 6.94 in 2022 and to 8.23 in 2023.

Table 4. Average NUM Score for Each Province in Java

	2021		2022		2023	
No	Province	Score	Province	Score	Province	Score
1	DKI Jakarta	53.89	DIY	58.50	DIY	64.39
2	DIY	53.86	DKI Jakarta	57.64	DKI Jakarta	62.39
3	Central Java	52.03	Central Java	54.47	Central Java	60.95
4	East Java	50.24	West Java	52.38	East Java	57.53
5	West Java	49.47	East Java	52.14	West Java	56.30
6	Banten	49.37	Banten	51.56	Banten	56.16

Overall, numeracy scores across all aspects increased during the 2021-2023 period, indicating a positive trend in the learning process year after year. However, a significant gap in numeracy scores between regions still occurs. This disparity can be caused by several factors, such as differences in teacher and school quality, the availability of learning facilities, accessibility to learning resources, and technical factors like variations in the size and composition of samples from each region. Therefore, sustained and targeted efforts are essential to reduce disparities between regions and improve the equity of education quality.

Clustering

Table 5. DBI Score 2021

Number of Clusters	DBI Score
2	0.715770
3	0.711491
4	0.543961
5	0.574736
6	0.639801
7	0.567050
8	0.589554
9	0.657457
10	0.713217

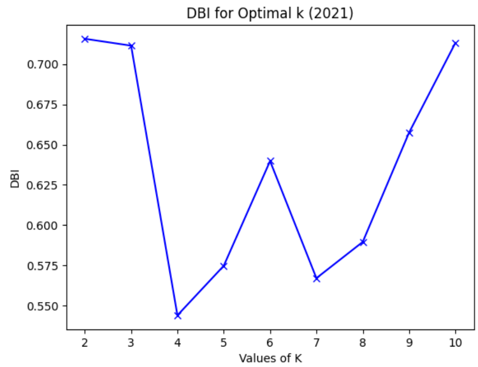

Figure 7. DBI Score 2021

Table 6. DBI Score 2022

Number of Clusters	DBI Score
2	0.616860
3	0.579215
4	0.469287
5	0.560565
6	0.589835
7	0.669399
8	0.693224
9	0.729867
10	0.703823

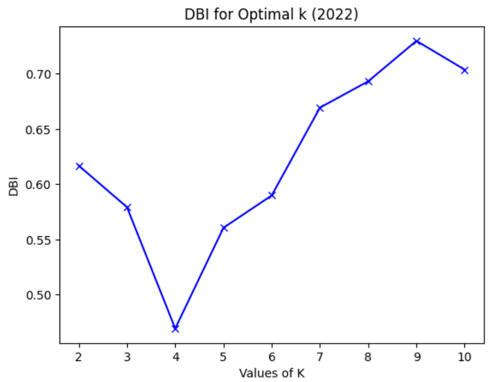

Figure 8. DBI Score 2022

Table 7. DBI Score 2023

Number of Clusters	DBI Score
2	0.739795
3	0.767287
4	0.837971
5	0.866033
6	0.761890
7	0.739853
8	0.761530
9	0.802851
10	0.894526

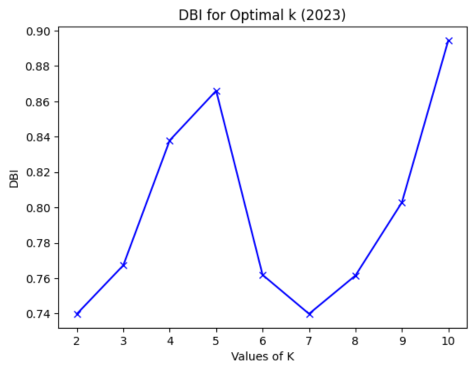

Figure 9. DBI Score 2023

Based on the DBI principle in determining the optimal number of clusters, namely the cluster with the lowest DBI result, the number of clusters is set at four clusters for 2021 and 2022, and two clusters in 2023. The decrease in the number of clusters from four to two in 2023 may indicate an increasing tendency for homogeneity or uniformity of numeracy scores between regencies/cities on the island of Java, or in other words, the variation in scores between regencies/cities tends to decrease.

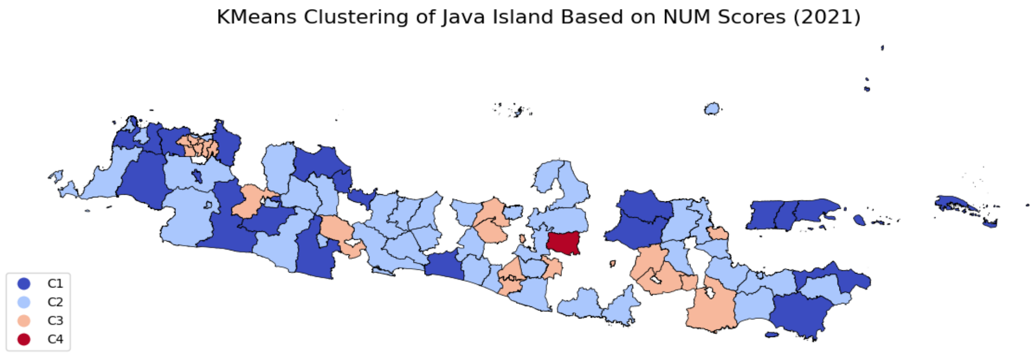

Figure 10. K-Means Clustering of Java Island Based on NUM Scores (2021)

Table 8. K-Means Clustering of Java Island Based on NUM Scores (2021)

Variable	Cluster C1	Cluster C2	Cluster C3	Cluster C4
Cluster Members	18	42	21	1
Mean NUM	46.16	50.51	54.57	66.15
Mean NUM_ALJ	44.58	49.39	53.62	63.16
Mean NUM_GEO	45.88	49.46	52.01	62.81
Mean NUM_BIL	46.05	50.70	54.99	66.98
Mean NUM_DAT	46.45	51.06	55.00	66.96
Mean NUM_L1	44.27	49.14	53.40	66.54
Mean NUM_L2	46.28	50.30	54.40	65.76
Mean NUM_L3	47.50	51.60	54.92	65.09

In 2021, the majority of regencies/cities in Java were grouped into cluster C2. Cluster C4 has the highest average score and only has one member, Sragen Regency. Meanwhile, cluster C1 has the lowest average score, dominated by regions from West Java and East Java Provinces. Interestingly, no regions from DKI Jakarta or Yogyakarta are included in this cluster.

Compared to the overall average for Java, clusters C1 and C2 have average scores below the overall average across all domains and cognitive levels, while clusters C3 and C4 have average scores above the overall average across all domains and cognitive levels. Unfortunately, the majority of regions are still included in clusters C1 and C2, indicating the persistently low numeracy skills in a significant number of regencies/cities in Java.

Of the four numeracy domains, the Data and Uncertainty domain had the highest average scores in each cluster. This is consistent with the overall data for Java, where this domain also had the highest scores in 2021. Meanwhile, clusters

C1 and C2 had the lowest scores in the Algebra domain, while clusters C3 and C4 had the lowest scores in the Geometry domain. This indicates that the ability to understand data and uncertainty is relatively strong, while algebra remains a weakness in the lower clusters, and geometry is a weakness in the higher clusters.

From the cognitive level, knowing competency (L1) is the lowest in clusters C1, C2, and C3, while reasoning competency (L3) is the highest in these clusters. This aligns with the overall average results for Java, where reasoning competency (L3) received the highest average and knowing competency (L1) received the lowest average. However, this result is reversed in cluster C4, where knowing competency (L1) received the highest score, and reasoning competency (L3) received the lowest score. This may indicate that high numeracy skills are not only caused by critical thinking skills, but also by strong mastery of basic concepts.

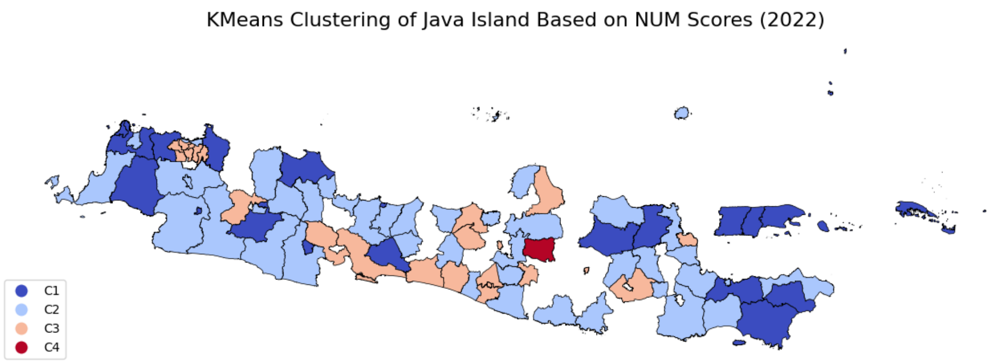

Figure 11. K-Means Clustering of Java Island Based on NUM Scores (2022)

Table 9. K-Means Clustering of Java Island Based on NUM Scores (2022)

	Cluster			
Variable	C1	C2	C3	C4
Cluster Members	19	39	23	1
Mean NUM	46.71	52.22	59.22	72.80
Mean NUM_ALJ	45.80	52.01	58.75	70.08
Mean NUM_GEO	45.90	51.72	58.12	70.41
Mean NUM_BIL	46.24	51.27	57.49	70.44
Mean NUM_DAT	45.06	50.67	57.49	69.59
Mean NUM_L1	45.05	50.92	58.58	73.85
Mean NUM_L2	48.30	53.76	59.670	68.57
Mean NUM_L3	45.69	51.05	57.13	67.97

The clustering pattern in 2022 was similar to the previous year, with Cluster C2 remaining the most numerous, and Sragen Regency remaining the sole member of Cluster C4. However, positive shifts were observed in several regions, such as Bogor City and Situbondo Regency, which previously ranked in the lowest cluster (C1), moving up to Cluster C2, and Kebumen Regency, which rose from cluster C1 to Cluster C3. Conversely, several regions experienced a decline from Cluster C2 to Cluster C1.

The numeracy domain showed significant changes compared to the previous year. The Data and Uncertainty domain, which had the highest scores in each cluster in the previous year, was the lowest this year. Conversely, the Algebra domain, which in the previous year had the lowest scores in clusters C1 and C2, showed significant improvement this year and became the highest-scoring domain in clusters C2 and C3. Meanwhile, the Geometry domain held the highest position in cluster C1, and the Number domain held the highest position in cluster C4. This shift indicates that the improvement in numeracy skills this year was more evenly distributed across various domains compared to the previous year, which was more concentrated in a single domain.

In terms of cognitive level, cluster C4 exhibited similar characteristics as the previous year, with the knowing competency (L1) having the highest score and the reasoning competency (L3) the lowest. Meanwhile, in clusters C1 and C2, the knowing competency (L1) remained the lowest-scoring competency, while the reasoning competency (L3) was the lowest in cluster C3. Furthermore, the applying competency (L2) was the highest-scoring competency in clusters C1, C2, and C3, indicating an emphasis on applying competency this year.

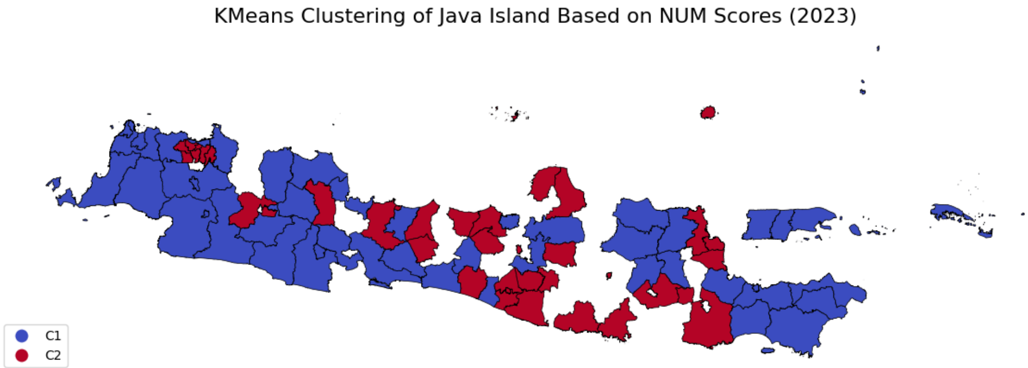

Figure 12. K-Means Clustering of Java Island Based on NUM Scores (2023)

Table 10. K-Means Clustering of Java Island Based on NUM Scores (2023)

Variable	Cluster C1	Cluster C2
Cluster Members	46	36
Mean NUM	54.16	63.89
Mean NUM_ALJ	53.83	64.53
Mean NUM_GEO	54.39	59.91
Mean NUM_BIL	53.20	63.43
Mean NUM_DAT	54.48	65.35
Mean NUM_L1	47.72	60.01
Mean NUM_L2	54.12	64.28
Mean NUM_L3	54.10	63.16

In 2023, the clustering results were quite different from previous years, with the number of clusters decreasing from four to two. Cluster C1 had a lower average score and a larger number of members than cluster C2. Geographically, cluster C2 is more concentrated in the central region of Java, with most of its members coming from Central Java Province. Meanwhile, cluster C1 appears more dispersed, with the majority of its members coming from West Java and East Java Provinces. Furthermore, the majority of areas in the provinces of DKI Jakarta, Yogyakarta, and Central Java are included in cluster C2. In fact, DKI Jakarta and Yogyakarta have only one regency/city included in cluster C1: North Jakarta and Kulon Progo Regency.

In terms of numeracy, the Data and Uncertainty domain has improved again and become the domain with the highest scores. Meanwhile, cluster C1 has the lowest score in the Number domain, while cluster C2 has the lowest score in the Geometry domain. This indicates that the Data and Uncertainty domain is the most mastered numeracy skill, while number skills remain a weakness in the lower cluster, and geometry is a weakness in the higher cluster. Meanwhile, when viewed from the cognitive level, this year, all clusters appear to share similar characteristics, with knowing competency (L1) being the lowest competency and applying competency (L2) being the highest.

Overall, the 2023 clustering results show a trend toward more equitable numeracy skills across regions on Java compared to previous years, although disparities remain. Sragen Regency consistently ranks among the clusters with the highest average scores, followed by areas in the Yogyakarta and DKI Jakarta Provinces. Conversely, several regions in Banten, West Java, and East Java provinces consistently rank among the lowest clusters. This pattern indicates that despite improvements and some level of equitable distribution, disparities in numeracy skills persist across regions. In addition, the fact that the majority of regions are still included in the cluster with a low average score shows that improving numeracy skills is still a big challenge, especially for regions that are consistently in the lower cluster.

The clustering results from 2021 to 2023 show an important pattern in the distribution of numeracy skills across Java Island. Although the decrease in the optimal number of clusters may suggest an increase in homogeneity, the reality is that a gap still exists, and the majority of regions remain within the low-performing clusters. This highlights the urge for more targeted learning interventions, considering that not all regions can be treated equally. Furthermore, these findings offer valuable insight for policymakers to identify the specific needs of each region, particularly those consistently grouped in the lower clusters.

Conclusion

The results of the study indicate that the numeracy skills of high school students in Java have increased from year to year, both overall and in each domain and cognitive level. Variations in the pattern of abilities in each domain tend to fluctuate from year to year, while the cognitive level shows a more stable pattern, where the competence of knowing tends to have a lower score than the competence of applying and reasoning. Based on the results of clustering using the K-Means algorithm with Davies-Bouldin Index (DBI) evaluation, the optimal number of clusters formed is four clusters for 2021 and 2022, and two clusters for 2023. This decrease in the number of clusters may indicate an increasing trend of increasing equality of numeracy skills between regions in Java. However, the fact that each year the majority of regions are still included in the cluster with low scores, and the disparities and gaps that still occur between regions indicate the importance of efforts to improve numeracy skills and educational equality comprehensively and sustainably, especially for regions that are consistently in the cluster with low scores.

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