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Clustering Regional Educational Performance in Indonesia Using K-Means

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Abstract: This study examines regional disparities in educational development across Indonesia by clustering 38 provinces based on indicators of SDG 4 (Quality Education). Using the *k*-means algorithm with $k = 4$, the analysis identifies groups of provinces with similar educational profiles to support evidence-based policymaking. The resulting clusters reveal substantial heterogeneity. Cluster 1 (highly disadvantaged) consists of Papua Pegunungan and Papua Tengah, which exhibit the lowest national performance across schooling and attendance indicators. Cluster 2 (disadvantaged) includes 20 provinces with low to moderate achievement levels, including short average schooling duration and low upper-secondary completion. Cluster 3 (advanced) comprises 15 provinces with relatively strong educational outcomes. Cluster 4 (highly advanced) is represented solely by the Special Region of Yogyakarta, demonstrating markedly superior performance. These findings highlight persistent educational inequality and suggest differentiated policy priorities. Interventions for lagging clusters should focus on improving access, teacher quality, and infrastructure, particularly in remote and disadvantaged regions. By providing an empirically derived typology of provincial education performance, this study contributes to better-targeted strategies for achieving SDG 4 and reducing regional disparities in Indonesia.

1. INTRODUCTION

Education plays a crucial role in human and social development, making its quality a common benchmark for a nation's progress [1], [2]. The importance of education is reflected in the Sustainable Development Goals (SDGs), where Goal 4 specifically emphasizes ensuring inclusive and equitable quality education and promoting lifelong learning opportunities for all. The Government of Indonesia has launched various programs to achieve this goal, such as the 12-year compulsory education program and the allocation of at least 20% of the national budget for education. Thanks to these efforts, several national education indicators have shown improvement over the years. For instance, the national average years of schooling, or in Bahasa: rata-rata lama sekolah (RLS) has steadily increased, and school participation rates, or

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in Bahasa: angka partisipasi sekolah (APS) in many regions are nearing universality at the primary school level.

Nevertheless, Indonesia continues to face major challenges in achieving equitable education. Significant disparities remain between regions, particularly between urban and rural areas and between the western and eastern parts of the country. Luthfi et al. [3] identify several persistent barriers, including unequal access to education, low teacher quality, and limited educational infrastructure, all of which hinder progress toward inclusive education. In the Province of West Nusa Tenggara, or in Bahasa: Nusa Tenggara Barat (NTB), for example, although participation rates have increased, disparities in educational achievement between districts and cities remain evident. Similar conditions occur nationally, where some provinces lag far behind more advanced provinces in key education indicators.

To better understand the pattern of these disparities, cluster analysis can be utilized. Cluster analysis groups objects (in this case, provinces) into clusters based on similarities in their characteristics. Through this technique, provinces with similar educational profiles will fall into the same cluster, facilitating the identification of patterns and profiling of educational development levels across groups. The resulting classifications can help policymakers understand regional characteristics and formulate more targeted interventions.

Previous studies have applied cluster analysis to various development indicators. Ulkhaq and Adyatama [4] and Ulkhaq [5] combined several clustering methods to cluster countries based on happiness index. Ulkhaq [6] used clustering to cluster countries according to their logistics performance. Utami et al. [7] used shopping and time attitudes to cluster food shoppers, while Minako et al. [8] used clustering technique to cluster internet shoppers. Suraya and Wijayanto [9] combined hierarchical and non-hierarchical clustering methods to group Indonesian provinces based on stunting indicators, identifying four clusters including single-member clusters. Hanifah and Primandari [10] applied *k*-means clustering to high school education indicators in NTB and identified four regional clusters ranging from high to very low educational categories. Meanwhile, Mustakim and Kamal [11] classified 34 provinces based on 11 parameters of secondary education management, resulting in three clusters in which only two provinces belonged to the best-performing cluster, while the rest were categorized as moderate or low. These findings illustrate that only a small number of regions meet high-quality education standards, emphasizing the need for stronger efforts to support other provinces. The authors of these studies highlight the importance of improving educational facilities, enhancing teacher quality, and providing special attention to underdeveloped regions.

Based on this background, the present study aims to apply the *k*-means clustering method to group Indonesian provinces according to education indicators related to SDG 4. Through this clustering process, provinces with similar characteristics—such as those with high, medium, low, or very low educational achievement—can be identified. The results will provide an overview of the distribution of SDG 4 achievement across Indonesia and can serve as a basis for developing strategies to improve educational equity tailored to the needs of each cluster. This study uses the most recent data (2024) and covers all provinces in Indonesia (38 provinces following the administrative expansion in Papua), thereby capturing the latest regional conditions in educational performance. Thus, the study not only contributes

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academically through methodological application but also offers practical value for education stakeholders in supporting the achievement of SDG 4 targets by 2030.

2. METHODOLOGY

2.1. Data and Variables

This study uses secondary data for the year 2024, covering 38 provinces in Indonesia (including newly established provinces in Papua). The data were obtained from publications of Statistics Indonesia (BPS) [12], [13], [14], [15] focusing on education indicators aligned with SDG 4 on quality education. The variables used include:

- School Participation Rate (APS) for age groups 7–12 (primary school), 13–15 (junior secondary), 16–18 (senior secondary), and 19–23 (higher education), representing the percentage of individuals in each age group who are currently attending school;
- Net Enrollment Ratio, or in Bahasa: angka partisipasi murni (APM) by education level (primary, junior secondary, senior secondary, higher education) expressed as the female-to-male ratio, reflecting gender parity in educational access (a value of 100 indicates perfect parity, values above 100 indicate higher female participation, and values below 100 indicate the opposite);
- Average Years of Schooling (RLS), representing the average number of completed years of schooling among individuals aged ≥25 years; and
- Expected Years of Schooling, or in Bahasa: harapan lama sekolah (HLS), representing the estimated duration of formal education expected for a 7-year-old child today.

These variables were selected because they represent educational outcomes across multiple levels and correspond to SDG 4 indicators.

2.2. Preprocessing and PCA

All numerical variables were standardized using *Z*-scores before clustering to prevent scale differences among indicators from causing dominance by any single variable. This ensures that each indicator contributes proportionally to the clustering process. In addition, principal component analysis (PCA) was conducted for dimensionality reduction and to address potential multicollinearity among variables.

The Kaiser-Meyer-Olkin test yielded an overall MSA of 0.667 (moderate but approaching an acceptable threshold), and Bartlett's test of sphericity was significant (χ^2 = 364.58, *p*-value < 0.001). These results indicate adequate correlations among variables for factor extraction, justifying the use of PCA. PCA results showed that four principal components (namely, PC1 to PC4) explained 86.8% of the total variance. The first component (PC1) accounted for 50.9% of the variance, dominated by high loadings on HLS, RLS, and APS across levels—representing a general dimension of "overall educational attainment." The second component (PC2) explained 16.9% of the variance, heavily influenced by APM ratio variables (particularly APM at the senior secondary and higher education levels), indicating a dimension related to gender disparities in educational access.

While PCA helped identify the underlying structure of the data, the *k*-means algorithm was ultimately performed on the standardized variables in their original dimensionality to

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maintain interpretability of the raw indicators. The PCA findings served mainly as a diagnostic tool to understand the primary differentiating factors among clusters.

2.3. *k*-Means Clustering Procedure

k-means clustering was employed to group provinces based on similarities in their educational profiles. The algorithm partitions observations into k clusters by iteratively minimizing intra-cluster variance, defined as the sum of squared distances between each data point and its respective cluster centroid. Centroids are initialized randomly and updated in each iteration until convergence—when changes in centroid positions become negligible. Through this process, provinces with comparable educational indicator patterns are assigned to the same cluster.

The algorithm of the *k*-means clustering used in this study is as follows:

Algorithm 1. *k*-means clustering

Input: Dataset $X = \{x_1, x_2, \ldots, x_n\}$; number of clusters k

Steps:

1. Initialize k centroids $\mu_1, \mu_2, \ldots, \mu_k$ (chosen at random).

2. Repeat until convergence:

   a. Assignment step:

   For each data point x_i:

   Assign x_i to the cluster whose centroid is closest

$$C(i) = \arg\min_j \left\| x_i - \mu_j \right\|^2 \quad (1)$$

   b. Update step:

   For each cluster $j = 1, \ldots, k$:

   Recompute centroid as the mean of points in that cluster

$$\mu_j = \frac{1}{|C_j|} \sum_{x_i \in C_j} x_i \quad (2)$$

3. Convergence criterion:

   Stop when cluster assignments no longer change or when centroid movement is below a small threshold ε.

Return: Final cluster assignments C; centroids μ

Output: Cluster assignments C; cluster centroids μ

A critical step in the *k*-means procedure is determining the optimal number of clusters (k). This study applied several evaluation criteria, including the Elbow Method, the Silhouette Score, and the Davies–Bouldin Index as an additional diagnostic.

Using the Elbow Method, the Within-Cluster Sum of Squares (WSS) was computed across various k values. The “elbow point”—the stage at which reductions in WSS begin to

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level off—signals an appropriate number of clusters. As illustrated in Figure 1, WSS decreases sharply up to $k = 4$, after which the decline becomes more gradual (the drop from $k = 4$ to $k = 5$ is notably smaller than the drop from $k = 2$ to $k = 4$). This trend suggests that $k = 4$ is a plausible solution.

The Silhouette Coefficient (s) was then used to evaluate clustering quality across different values of k. This coefficient measures cohesion and separation, with values near +1 indicating distinct and well-separated clusters, and values near 0 or negative indicating overlap or misclassification. As shown in Figure 2, the highest silhouette score appears at $k = 2$ ($s \approx 0.67$). However, a two-cluster solution is overly coarse, as it divides the provinces into only two broad groups. Among solutions with $k \geq 3$, the highest silhouette score occurs at $k = 3$ ($s \approx 0.62$), followed by $k = 4$ ($s \approx 0.28$). Despite its lower score, the $k = 4$ solution was retained because it provides more granular differentiation—allowing, for example, clearer identification of high-performing and low-performing clusters. This choice aligns with methodological recommendations that cluster determination should consider both statistical indicators and substantive research objectives. Therefore, $k = 4$ was selected as the final number of clusters, balancing interpretability with acceptable cluster separation.

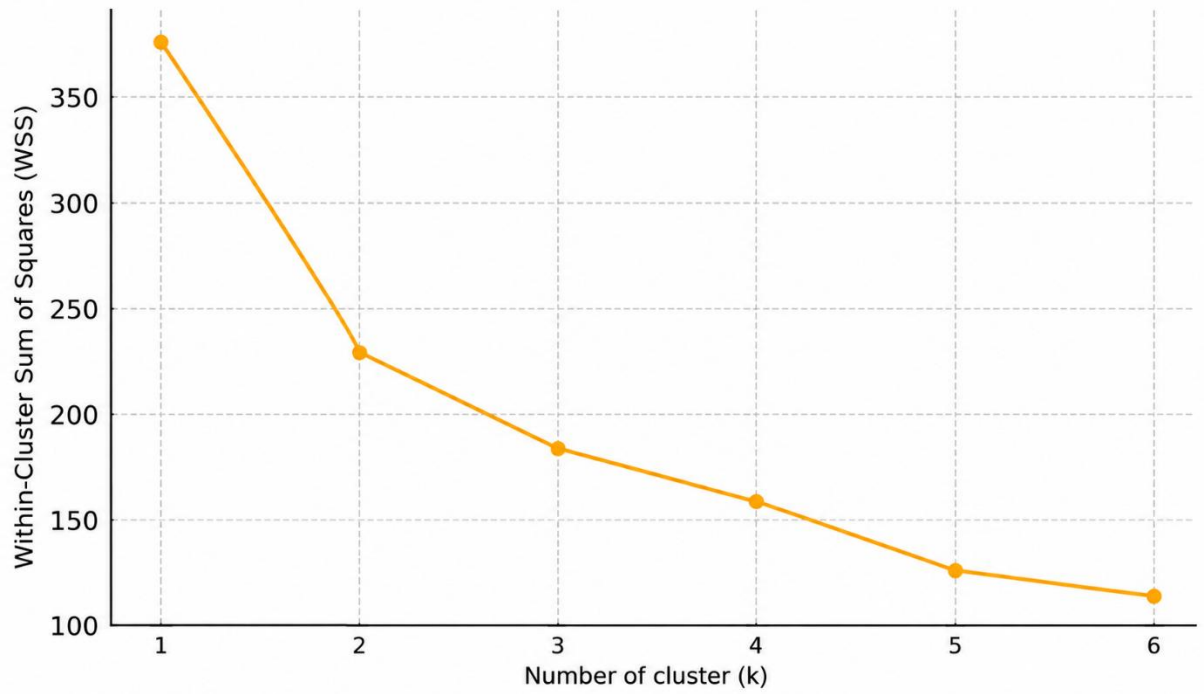


Figure 1. Elbow graph

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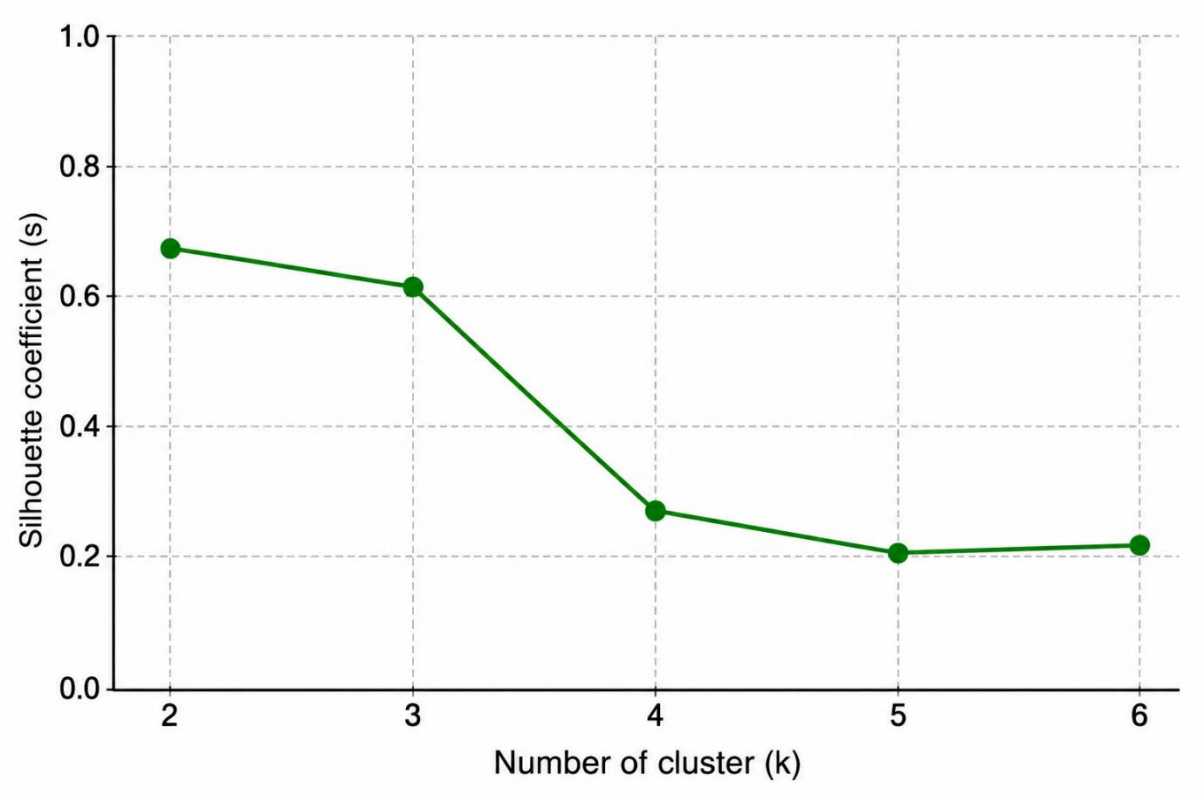


Figure 2. Silhouette coefficient graph

Once k was selected, cluster interpretation was conducted by examining cluster centroids and descriptive statistics (e.g., mean values of each educational indicator) to identify the defining characteristics of each group. Clusters were subsequently assigned qualitative labels (e.g., "high-performing," "moderate," "lagging"). Comparative visualizations, including tables and graphs, were used to present differences among the clusters clearly. All analyses were performed using R software, with cross-platform verification conducted to ensure the robustness of the results.

3. RESULTS AND DISCUSSION

Using $k = 4$, k-means produced a more granular and interpretable partition of Indonesian provinces. The four clusters represent distinct levels of educational development: Cluster 1 (Highly Disadvantaged), Cluster 2 (Disadvantaged), Cluster 3 (Advanced), and Cluster 4 (Highly Advanced). To avoid interpretive ambiguity, clusters are ordered by increasing educational attainment rather than by the arbitrary numeric labels returned by the algorithm. Table 1 summarizes the mean values of key indicators for each cluster, while Figure 3 depicts their distribution in the RLS–HLS feature space. Compared with the $k = 3$ solution, the four-cluster structure reduces within-group heterogeneity and produces clearer separation, particularly for provinces at both extremes of the education distribution.

The RLS–HLS scatter plot shows distinct group boundaries. DI Yogyakarta, positioned in the upper-right quadrant with an HLS of 15.7 years, appears as a high-performing outlier forming its own cluster (Cluster 4). In contrast, Papua Pegunungan and Papua Tengah

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consistently occupy the lower-left region and are isolated within Cluster 1 due to extremely low RLS and HLS values. Clusters 2 and 3 occupy intermediate regions, with Cluster 3 systematically positioned higher along both axes, indicating stronger educational outcomes. Profile for each cluster is shown in Table 1.

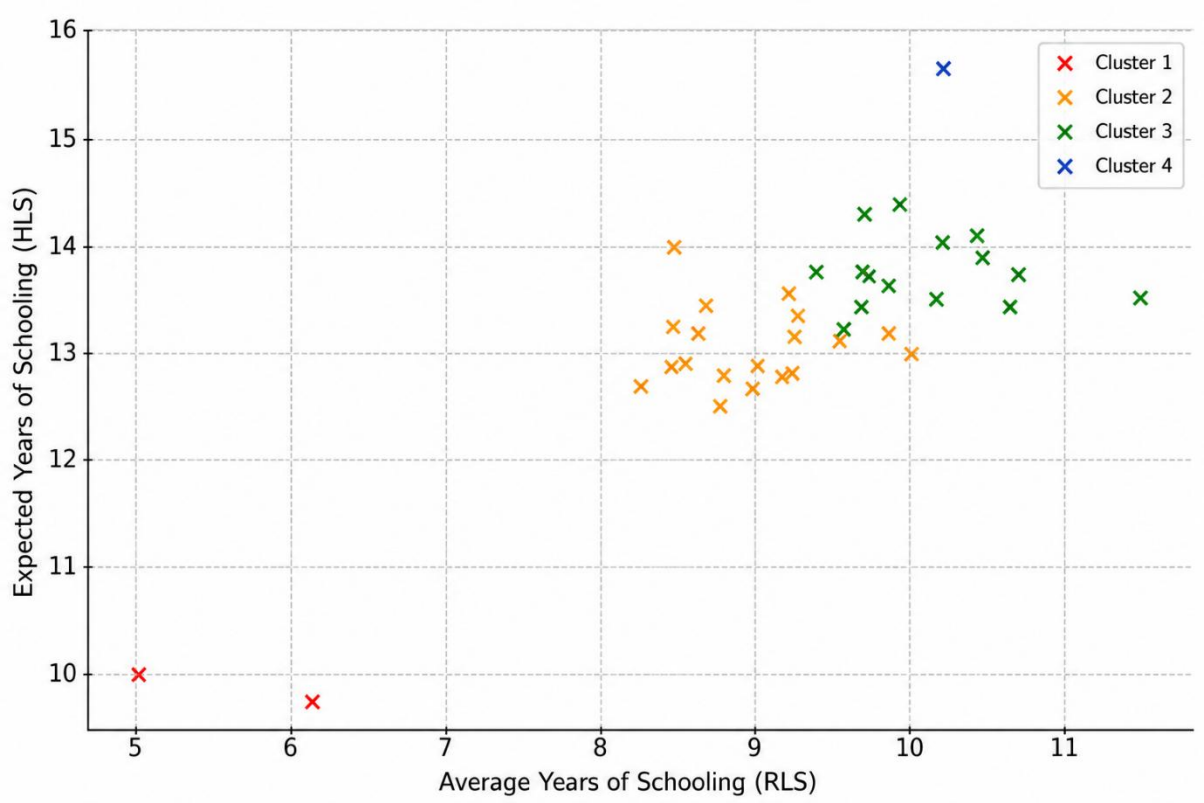


Figure 3. HLS vs RLS for four formed clusters

Table 1. Profile of clusters

Cluster (number of province)	RLS (years)	HLS (years)	APS 7–12 (%)	APS 16–18 (%)	APS 19–23 (%)	Ratio APM High Senior School F/M (%)
Cluster 1 (2 provinces)	5.64	9.80	77.3	51.9	17.9	98.0
Cluster 2 (20 provinces)	9.12	13.09	99.2	73.9	27.8	102.1 (F > M in Junior High School)
Cluster 3 (15 provinces)	10.16	14.00	99.3	80.9	36.7	102.5 (F > M)
Cluster 4 (1 province: DIY)	10.23	15.70	99.9	90.4	54.2	99.1

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Cluster 1 (Highly Disadvantaged) contains only two provinces—Papua Tengah and Papua Pegunungan—representing the lowest educational performance nationally. Their average RLS (5.6 years) and HLS (9.8 years) lie far below the national mean (HLS = 13.21 years). Nearly half of the adult population has not completed primary education. School participation among school-age children is also critically low: APS for primary education is 77%, APS for senior secondary is 52%, and tertiary participation is only 18%.

These results are consistent with long-standing evidence on the severe educational disparities in the Papua highlands, shaped by geographic remoteness, limited school infrastructure, teacher shortages, and socioeconomic deprivation. The structural nature of these constraints suggests that incremental interventions are unlikely to produce rapid gains. Instead, transformative, multisectoral strategies—e.g., construction of boarding schools, deployment of incentivized teacher placements, dropout-prevention programs, and affirmative action scholarships—are essential to accelerate progress toward SDG 4 in this region.

Cluster 2 (Disadvantaged), comprising 20 provinces, includes regions with low-to-moderate educational attainment and represents the largest group in the cluster solution. Provinces in this category span Java (e.g., West, Central, and East Java, Banten), Eastern Indonesia (NTB, NTT, Gorontalo, Central and West Sulawesi), several Kalimantan provinces, and two recently formed Papua provinces (South Papua and West Papua).

The cluster is characterized by RLS values between 8.5 and 9.5 years and an HLS near 13.0 years, implying that children in these provinces are projected to complete upper secondary school on average. APS for primary and junior secondary levels remains high (98% and 94%, respectively), but APS for senior secondary declines substantially to 73%. This suggests that approximately one-quarter of adolescents either discontinue schooling after junior secondary or do not transition to the upper secondary level. Tertiary participation is also limited (APS 19–23 years = 28%).

The challenges faced by Cluster 2 provinces are diverse, including financial constraints (early entry into the labor market, unaffordable education costs), geographic barriers (rural and remote areas), and uneven distribution of senior secondary schools. In some provinces, gender disparities persist; for example, South Papua exhibits a pronounced gap in senior secondary GER where female participation is significantly lower than that of males. These findings highlight the need for targeted gender-responsive policies.

Strengthening the effectiveness of Indonesia's 12-Year Compulsory Education Program is crucial for this cluster. Recommended strategies include expanding vocational school networks in underserved areas, providing conditional cash transfers and scholarships to at-risk households, and enhancing the quality and relevance of upper secondary education. For provinces with gender gaps, dedicated scholarship schemes and community outreach programs targeting girls' education are required.

Cluster 3 (Advanced) consists of 15 provinces with educational outcomes above the national average but not at the very top of the distribution. Their average RLS is 10.1 years, indicating that most adults have completed junior secondary and a large proportion have completed senior secondary school. HLS is 13.8 years, projecting continuation into early tertiary levels. APS values for primary (99%) and junior secondary (97%) reflect near-universal

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enrollment; APS for senior secondary is 80%, and tertiary APS reaches 34%, substantially exceeding Cluster 2.

The provinces in Cluster 3 include advanced regions across Sumatra (Aceh, North Sumatra, West Sumatra, Riau, Bengkulu, Riau Islands), Java and Bali (Jakarta, Bali), Kalimantan (East and North Kalimantan), Sulawesi (Southeast Sulawesi), and Eastern Indonesia (Maluku, North Maluku, Papua, Southwest Papua). The presence of Papua (parent province) and Southwest Papua indicates strong performance in urbanized centers such as Jayapura and Sorong, in contrast with highland regions.

Cluster 3 can broadly be categorized as "educationally advanced provinces." These regions have largely achieved equitable basic and secondary education outcomes. Remaining challenges include increasing tertiary enrollment and improving overall educational quality to meet global benchmarks. Potential strategies include expanding scholarship and government-bonded programs for tertiary education, encouraging high-quality universities to establish satellite campuses, improving teacher competency, and strengthening school–industry partnerships to support vocational pathways.

Cluster 4 (Highly Advanced) is a single-province cluster consisting solely of DI Yogyakarta. This province stands out as a structural outlier due to exceptionally high educational performance. Yogyakarta records the highest HLS in Indonesia (15.70 years), indicating that children are projected to complete diploma-level or early undergraduate education. APS for senior secondary school is 90.36%—the highest nationally—and tertiary APS reaches 54%, nearly double the national average (29%). RLS is also high at 10.23 years, although slightly below Jakarta's, likely due to demographic factors (a large elderly population with lower historical educational attainment).

Yogyakarta's strong educational culture, dense concentration of reputable higher education institutions, and long-standing reputation as Indonesia's "education city" contribute to its status. Prior studies similarly identify Yogyakarta as a positive outlier in other development indicators. As such, Cluster 4 may be interpreted as representing a "best-practice model" for educational development in Indonesia.

Policy lessons from Yogyakarta include prioritizing teacher quality, providing broad financial access to education, maintaining supportive learning environments, and fostering collaboration between schools and universities. National-level initiatives could include leveraging Yogyakarta as a mentoring hub for other provinces through teacher-exchange programs, school twinning, and joint educational planning. The results demonstrate that achieving SDG 4 targets at a high level is attainable when the educational ecosystem is well-integrated and consistently supported.

Several policy implications emerge from these findings. Prioritize resource allocation for Clusters 1 and 2, particularly through expanding school infrastructure in remote/3T (frontier, outermost, disadvantaged) areas, providing high-quality teachers with incentive structures, promoting community learning centers, and offering affirmative scholarships for students from these regions. For Cluster 3 (advanced), the policy emphasis should shift from access to quality enhancement, including strengthening teacher competencies, aligning curricula with global standards, and improving pathways to higher education and vocational

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training—supported by partnerships with industry to improve graduate employability. Cluster 4 (highly advanced) can serve as a national benchmark and innovation hub. Provinces such as DIY may be mobilized to disseminate best practices through school twinning programs, technical assistance, and inter-provincial collaboration.

4. CONCLUSION

This study classified 38 Indonesian provinces based on SDG 4 (Quality Education) indicators using the *k*-means clustering method. The optimal solution, k = 4, produced four distinct groups with markedly different educational profiles. Cluster 1 (severely lagging) comprises Papua Pegunungan and Papua Tengah, the two provinces with the lowest educational outcomes nationwide. Cluster 2 (lagging) includes 20 provinces characterized by low to moderate performance, reflected in an average schooling duration of 8–9 years and a substantial proportion of youth not completing upper-secondary education. Cluster 3 (advanced) consists of 15 provinces with relatively strong performance (average schooling duration of approximately 10 years; upper-secondary net attendance around 80%). Cluster 4 (highly advanced) is represented solely by the Special Region of Yogyakarta (DIY), which demonstrates educational outcomes far exceeding the national average.

These clusters underscore the persistence of substantial regional disparities in Indonesia's educational development, ranging from areas approaching ideal SDG 4 benchmarks to those still struggling to achieve foundational levels. Overall, higher clusters (from 1 to 4) are associated with progressively stronger educational infrastructure, better input quality, and stronger linkages with economic development. Provinces in the lagging clusters also tend to exhibit higher poverty rates and limited infrastructure, highlighting the need for cross-sectoral efforts to address structural disadvantages.

Achieving SDG 4 at the national level requires elevating the lowest-performing clusters while continuing quality improvements in more advanced regions. Ensuring equitable and inclusive education policies is therefore essential, with targeted support for lagging provinces and sustained quality-driven reforms elsewhere. The cluster mapping presented in this study offers evidence-based insights to support such differentiated strategies, enabling policymakers to tailor interventions according to the unique needs of each cluster. With sustained and segmented policy measures, Indonesia may substantially narrow regional educational disparities by 2030 and move closer to realizing its commitment to inclusive and high-quality education for all.

REFERENCES

[1]. M. M. Ulkhaq, G. Oggioni & R. Riccardi, "How efficient are schools in South-East Asia? An analysis through OECD PISA 2018 data," Educational Research and Evaluation, vol. 30, no. 3-4, pp. 212-243, 2025.

[2]. M. M. Ulkhaq, G. Oggioni & R. Riccardi, "Two-stage super-efficiency model for measuring efficiency of education in South-East Asia," Decisions in Economics and Finance, vol. 47, no. 2, pp. 513-534, 2024.

[DOI: 10.14710/JCASE.vol1.iss2.904]

[3]. A. Luthfi, W. Poespitohadi, I. M. A. W. Putra, & D. I. Mawarni, "Quality education in achieving the SDGs in Indonesia," Jurnal Ilmu Sosial dan Ilmu Administrasi Negara (Mediasosian), vol. 9, no. 1, pp. 175-190, 2025.

[4]. M. M. Ulkhaq, & A. Adyatama, "Clustering countries according to the World Happiness Report 2019," Engineering and Applied Science Research, vol. 48, no. 2, pp. 137-150, 2021.

[5]. M. M. Ulkhaq, "Clustering countries according to the World Happiness Report," Statistica & Applicazioni, vol. XVIII, no. 2, pp. 197-220, 2020.

[6]. M. M. Ulkhaq, "Clustering countries according to the logistics performance index," Jurnal Teknik Informatika dan Sistem Informasi, vol. 10, no. 1, pp. 1010-1018, 2023.

[7]. A. A. Utami, A. G. Ginanjar, N. Fadlia, I. A. Lubis, & M. M. Ulkhaq, "Using shopping and time attitudes to cluster food shoppers: An empirical finding from Indonesia," Journal of Physics: Conference Series, vol. 1248, p. 012005, 2019. https://doi.org/10.1088/1742-6596/1284/1/012005

[8]. F. S. Minako, M. M. Ulkhaq, A. R. A. Pratiwi, D. 'Sa Nu, & P. Y. Akshinta, "Clustering internet shoppers: An empirical finding from Indonesia," Proceedings of the 2019 International Conference on E-business and Mobile Commerce (pp. 35-39). https://doi.org/10.1145/3332324.333232

[9]. G. R. Suraya & A. W. Wijayanto, "Comparison of hierarchical clustering, k-means, k-medoids, and fuzzy c-means methods in grouping provinces in Indonesia according to the special index for handling stunting," Indonesian Journal of Statistics and Its Applications, vol. 6, no. 2, pp. 180-201, 2022.

[10]. S. Hanifah & A. H. Primandari, "Implementasi metode *k*-means clustering dalam pengelompokan kabupaten/kota di Provinsi NTB berdasarkan indikator Pendidikan," Emerging Statistics and Data Science Journal, vol. 1, no. 3, pp. 378-393, 2023.

[11]. Z. Mustakim & R. Kamal, "*k*-means clustering for classifying the quality management of secondary education in Indonesia," Cakrawala Pendidikan, vol. 40, no. 3, pp. 725-738, 2021.

[12]. BPS (2024a). Angka Partisipasi Sekolah (APS) menurut provinsi dan kelompok umur. From: https://www.bps.go.id/id/statistics-table/2/MjIxMSMy/angka-partisipasi-sekolah--aps--menurut-provinsi-dan-kelompok-umur.html

[13]. BPS (2024b). Rata-rata Lama Sekolah. From: https://www.bps.go.id/id/statistics-table/2/NDE1IzI=/-metode-baru-rata-rata-lama-sekolah.html

[14]. BPS (2024c). Harapan Lama Sekolah. From: https://www.bps.go.id/id/statistics-table/2/NDE3IzI=/-metode-baru--harapan-lama-sekolah--tahun-.html

[15]. BPS (2024d). Angka partisipasi murni (APM) menurut provinsi dan jenjang Pendidikan. From: https://www.bps.go.id/id/statistics-table/2/MzA0IzI=/angka-partisipasi-murni--apm--menurut-provinsi-dan-jenjang-pendidikan.html

[DOI: 10.14710/JCASE.vol1.iss2.904]