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A Cluster-Based Multi-Criteria Decision-Making Approach for Regional Economic Development Prioritization Using AHP–SAW

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ABSTRACT

Determining regional economic development priorities requires an analytical approach capable of accommodating regional heterogeneity and the complexity of macroeconomic indicators. This study aims to identify regional economic development priorities by integrating clustering techniques and a hybrid Analytical Hierarchy Process (AHP)–Simple Additive Weighting (SAW) method. The clustering approach is employed to group regions into relatively homogeneous clusters based on economic indicators, allowing for more context-sensitive priority analysis. Subsequently, the AHP method is applied to determine the relative importance of criteria within each cluster, while the SAW method is used to rank regional economic development alternatives. The study analyzes 38 regencies and municipalities in East Java using six macroeconomic indicators obtained from official Statistics Indonesia (BPS) publications. The results indicate that both criteria weights and priority development alternatives differ across clusters, reflecting variations in regional characteristics and economic challenges, such as the predominance of competitiveness issues in advanced regions, employment expansion in developing regions, and poverty alleviation along with the fulfillment of basic needs in underdeveloped regions. This approach enables more adaptive, objective, and data-driven development policy formulation. Conceptually, this study contributes to the development of a multi-criteria decision-making framework that supports the achievement of the Sustainable Development Goals (SDGs), particularly SDG 1 (No Poverty), SDG 8 (Decent Work and Economic Growth), and SDG 10 (Reduced Inequalities) and the Indonesia Emas 2045 Vision agenda, particularly in promoting inclusive and equitable regional economic development.

I. Introduction

Regional economic development is a crucial instrument for improving public welfare and reducing interregional disparities [1][2][3][4]. In the context of a large and diverse country such as Indonesia, regional economic development not only complements national development but also plays a key role in fostering inclusive and sustainable economic growth [5], [6]. Differences in social, economic, geographic, and demographic characteristics across regions lead to substantial variation in development capacity, potential, and challenges faced by each area [7]. As a result, uniform development policies tend to be less effective and may even exacerbate regional disparities if they are not tailored to specific regional conditions.

In the study of economic development, various macroeconomic indicators are commonly used to represent the performance and structure of regional economies [8][9][10][11]. Indicators such as income levels, economic growth rates, unemployment rates, poverty incidence, human resource quality, income inequality, and price stability reflect interrelated dimensions of development [12], [13], [14], [15], [16]. The diversity of these indicators highlights that regional economic development is a multidimensional phenomenon that cannot be adequately captured by a single indicator. However, the simultaneous use of multiple indicators also poses challenges in decision-making processes, particularly in determining the relative importance of each indicator and how they should be reconciled in formulating development priorities.

A clustering approach becomes relevant in addressing this complexity, as it enables regions to be grouped into relatively homogeneous clusters based on similarities in economic characteristics [15], [16], [17], [18], [19], [20]. Through clustering, regions with similar development patterns, challenges, and potentials can be analyzed within the same group, allowing planning and policy evaluation processes to be conducted in a more focused and contextual manner [20], [21], [22]. This approach helps avoid policy generalization and facilitates the formulation of more targeted development strategies aligned with the level of development and specific needs of each regional cluster.

Nevertheless, clustering results essentially provide information on regional groupings and do not directly address the key question of development priorities [23], [24], [25]. Once regions are grouped, a mechanism is still required to determine which indicators should be prioritized within each cluster and how alternative development policies can be ranked in a rational manner. Therefore, clustering needs to be integrated with multi-criteria decision-making methods capable of systematically processing multiple indicators and generating measurable priority rankings.

The Analytical Hierarchy Process (AHP) and Simple Additive Weighting (SAW) are two widely used multi-criteria decision-making methods for determining development policy priorities [24], [25], [26], [27], [28], [29], [30]. AHP is employed to determine criteria weights through a structured pairwise comparison process accompanied by consistency testing, thereby ensuring that the resulting weights have a strong rational foundation [31], [32], [33]. Meanwhile, the SAW method is used to rank development alternatives based on criteria weights and the performance values of each alternative [34], [35], [36]. SAW was selected due to its computational simplicity, transparency, and suitability for additive aggregation of weighted criteria, making it more interpretable for policy-oriented decision contexts compared to more complex outranking methods such as PROMETHEE or distance-based methods such as TOPSIS [37], [38], [39]. The integration of clustering with the hybrid AHP–SAW method enables the determination of regional economic development priorities that not only account for regional heterogeneity but also produce quantitative, adaptive, and cluster-specific policy recommendations.

Most previous studies on regional economic development prioritization have relied on aggregate approaches or directly applied multi-criteria decision-making methods without explicitly considering regional heterogeneity [9], [40], [41], [42]. In addition, the application of the SAW method is generally conducted in an aggregate manner across all criteria, resulting in limited insight into the individual contribution of each economic indicator to development priorities [43], [44], [45]. Consequently, a research gap remains in the development of prioritization models that integrate regional clustering processes with contextual multi-criteria analysis.

This study contributes to the achievement of the Sustainable Development Goals (SDGs), particularly SDG 1 (No Poverty), SDG 8 (Decent Work and Economic Growth), and SDG 10 (Reduced Inequalities). The clustering and hybrid AHP–SAW approach supports the formulation of more targeted and inclusive regional economic development policies. Furthermore, this study is relevant to the Indonesia Emas 2045 Vision agenda by strengthening evidence-based development planning aimed at achieving competitive and sustainable economic growth.

II. METHOD

A. Research Design and Data

This study employs a quantitative research design with a descriptive–analytical approach. This approach is used to describe regional economic conditions based on macroeconomic indicators and to analyze regional economic development priorities using multi-criteria decision-making methods. The data used in this study are secondary data obtained from official publications of the Statistics Indonesia (Badan Pusat Statistik/BPS) [46], [47].

The object of the study is the administrative regions of East Java Province, consisting of 38 regencies and municipalities, analyzed using six economic indicators: (1) gross regional domestic product (GRDP) per capita, (2) economic growth rate, (3) open unemployment rate, (4) percentage of poor population, (5) Human Development Index (HDI), and (6) Gini ratio. These indicators were selected because they represent key dimensions of economic growth, income distribution, human resource quality, and economic stability [48], [49], [50], [51], [52], [53], [54].

B. Regional Clustering

Clustering is employed to group regions based on similarities in economic indicator characteristics. The method used in this study is K-Means clustering, due to its ease of implementation and its effectiveness in handling numerical data [55], [56], [57]. Prior to clustering, all variables are standardized to prevent the dominance of certain indicators in the clustering process [58], [59]. The number of clusters is determined based on analytical considerations and evaluation of data variability. The clustering results yield several regional groups with relatively homogeneous economic characteristics [60], [61].

K-Means clustering is a non-hierarchical data grouping method that partitions observations into clusters by minimizing the distance between each data point and the cluster centroid. In this study, the Euclidean distance is used to measure the proximity between data points and cluster centroids, as expressed by the following equation [62], [63]:

$$d(x, y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$

where x_i represents the data point and y_i denotes the centroid coordinates.

C. Determination of Criteria Weights Using the Analytical Hierarchy Process (AHP)

At this stage, a pairwise comparison matrix among economic criteria is constructed for each cluster. The comparison matrix is then normalized to obtain the criteria weights, where each cluster has a distinct comparison matrix depending on the strength of the relationship between each variable and the proposed development solutions. The consistency of the judgments is evaluated using the Consistency Index (CI) and Consistency Ratio (CR), with CR ≤ 0.1 adopted as the threshold for acceptable consistency [29], [64].

$$CI = \frac{\lambda_{max} - n}{n - 1}$$

$$CR = \frac{CI}{RI}$$

D. Priority Determination Using the SAW Method

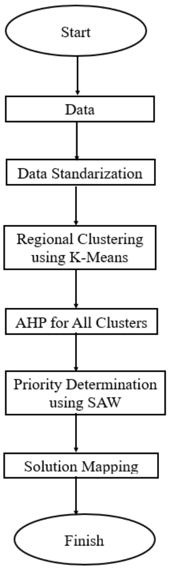

Figure 1. Research Method

The Simple Additive Weighting (SAW) method is employed to determine the priority of development alternatives for each cluster. In this study, SAW is applied separately to each criterion; therefore, for each cluster, six SAW matrices are constructed to represent the respective economic indicators. Normalization is performed by considering the type of criteria, namely benefit criteria (GRDP per capita, economic growth rate, and HDI) and cost criteria (unemployment rate, poverty rate, and Gini ratio). The final preference value is obtained by aggregating the normalized values weighted by the criteria weights derived from the AHP method. The overall research framework is illustrated in Figure 1.

III. RESULT AND DISCUSSION

A. Results of Regional Clustering

The results of the clustering analysis indicate that regions can be grouped into several clusters with distinct economic characteristics. Each cluster represents a relatively homogeneous level of economic development in terms of income levels, human resource quality, as well as inequality and economic stability.

Clustering was performed using the K-Means algorithm after standardizing all variables. The optimal number of clusters was determined using the Elbow Method, which indicated that a three-cluster solution provided the best balance between model simplicity and explanatory power. To validate the clustering results, the silhouette coefficient was calculated. The average silhouette score for the three-cluster solution was 0.57, indicating a reasonably well-defined clustering structure. The clustering results for the 38 regencies and municipalities in East Java Province are presented in Figure 2.

Based on Figure 2, three clusters are identified. Cluster 1 consists of 10 regions, namely Kediri City, Surabaya City, Malang City, Blitar City, Mojokerto City, Madiun City, Batu City, Pasuruan City, Sidoarjo Regency, and Gresik Regency. Cluster 2 comprises four regions, namely Bojonegoro Regency, Sampang Regency, Bangkalan Regency, and Sumenep Regency. Cluster 3 consists of 24 regions, including Probolinggo City, Pasuruan Regency, Mojokerto Regency, Kediri Regency, Malang Regency, Magetan Regency, Banyuwangi Regency, Tulungagung Regency, Blitar Regency, Madiun Regency, Lamongan Regency, Nganjuk Regency, Jombang Regency, Ponorogo Regency, Trenggalek Regency, Jember Regency, Lumajang Regency, Situbondo Regency, Probolinggo Regency, Tuban Regency, Bondowoso Regency, Ngawi Regency, Pacitan Regency, and Pamekasan Regency. The three clusters exhibit homogeneous characteristics within clusters and heterogeneous characteristics across clusters, as summarized in Table 1, which presents the comparison of average values among clusters.

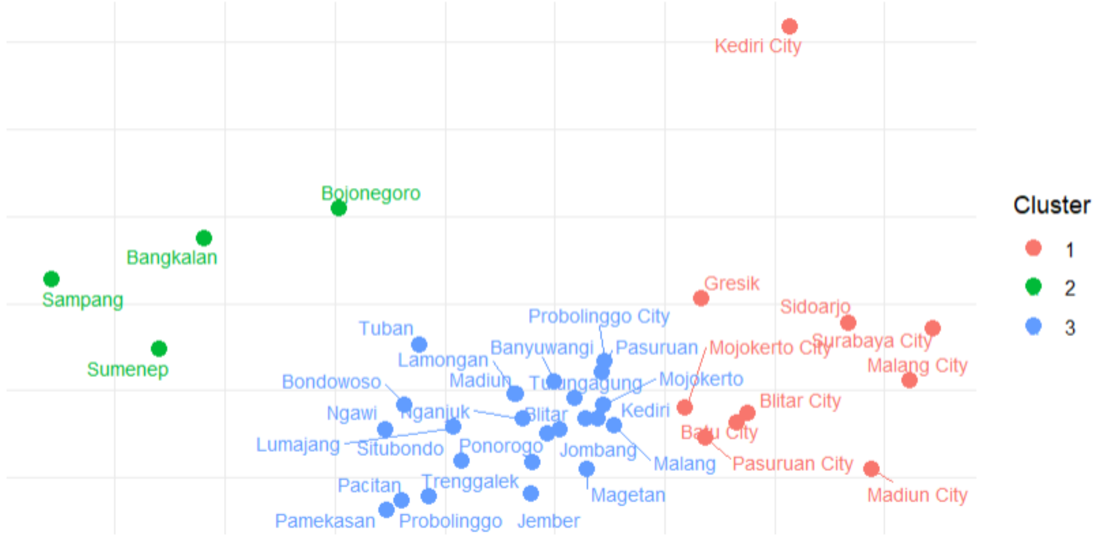

Figure 2. Visualization of K-Means Clustering Results for 38 Regencies/Municipalities in East Java

TABLE I
COMPARISON OF AVERAGE VALUES ACROSS CLUSTERS

Cluster	**Open Unemployment Rate**	**Human Development Index (HDI)**	**Percentage of Poor Population**	**GINI Ratio**	**GRDP per Capita**	**Economic Growth Rate**	**Number of Regions**
1	4.93	81.9	5.5	0.343	158.2	5.18	10
2	3.49	69.1	17.2	0.262	41.6	2.27	4
3	3.76	73.6	10.3	0.321	45.8	4.80	24

Based on Table 1, the clustering results form three regional clusters with distinct economic characteristics. Cluster 1 represents advanced regions, characterized by high GRDP per capita and HDI values as well as low poverty rates, although these regions still face relatively higher income inequality challenges. Cluster 2 reflects underdeveloped regions, exhibiting the lowest levels of GRDP per capita, HDI, and economic growth rates, along with the highest poverty incidence, thereby requiring more intensive basic development interventions. Meanwhile, Cluster 3 represents developing regions, with economic indicator values at moderate levels and relatively high economic growth rates, indicating considerable potential for development acceleration.

Overall, the clustering results confirm the presence of significant economic heterogeneity among the analyzed regions, suggesting that uniform development approaches are inappropriate. The classification of regions into three clusters provides an essential foundation for applying the hybrid AHP–SAW method to determine cluster-specific and context-sensitive development priorities. The AHP method is employed to determine the relative importance of economic indicators within each cluster according to their respective conditions and challenges, while the SAW method is used to rank economic development alternatives specific to each cluster. Consequently, the integration of clustering results with the AHP–SAW method enables the determination of regional economic development priorities that are more contextual, adaptive, and well-targeted.

B. *Criteria Weights Based on AHP*

Criteria weighting using the AHP method is conducted separately for each cluster to reflect differences in regional economic characteristics and development challenges. In the advanced region cluster, GRDP per capita and the Human Development Index (HDI) receive the highest weights, indicating that development efforts are focused on enhancing competitiveness and improving human resource quality, while the Gini ratio also receives considerable attention due to income inequality issues. In contrast, in the underdeveloped region cluster, the percentage of poor population, HDI, and the open unemployment rate emerge as the main priority criteria, reflecting the need for interventions targeting basic welfare and human development. Meanwhile, in the developing region cluster, the criteria weights are relatively more balanced, with greater emphasis on the economic growth rate and GRDP per capita as strategies to accelerate development and expand employment opportunities. Overall, the AHP results confirm that cluster-based criteria weighting provides a more rational and context-sensitive basis for decision-making and serves as a critical foundation for the application of the SAW method in determining regional economic development priorities.

The pairwise comparison matrices in the AHP process were constructed based on an extensive review of relevant literature, regional development frameworks, and national policy documents. The relative importance of each criterion was determined by synthesizing theoretical arguments and empirical findings related to regional economic development. Consistency testing was subsequently performed using the Consistency Index (CI) and Consistency Ratio (CR) to ensure the reliability of the judgment structure. All AHP pairwise comparison matrices satisfy the consistency requirement, with CR values below 0.1, indicating acceptable consistency. The results of the AHP-based weighting are presented in Table 2.

TABLE 2
AHP CRITERIA WEIGHTS FOR EACH CLUSTER

Criteria	Cluster 1 Advanced	Cluster 2 Underdeveloped	Cluster 3 Developing
Open Unemployment Rate	0.0939	0.1489	0.1537
Human Development Index (HDI)	0.2812	0.2364	0.1537
Percentage of Poor Population	0.0498	0.3469	0.0888
Gini Ratio	0.1521	0.0558	0.0559
GRDP per Capita	0.2709	0.0819	0.2739
Economic Growth Rate	0.1521	0.1301	0.2739
Total	1.0000	1.0000	1.0000

Based on Table 2, the criteria weighting results obtained using the AHP method reveal differences in the relative importance of economic indicators across regional clusters, reflecting variations in the characteristics and economic challenges of each cluster. These criteria weights are subsequently used as inputs in the SAW method to perform normalization and calculate the preference values of development alternatives. With cluster-specific AHP weights, the SAW method produces contextual rankings of development alternatives, whereby priorities in advanced clusters are directed toward enhancing competitiveness and improving human resource quality, in developing clusters toward accelerating economic growth and expanding employment opportunities, and in underdeveloped clusters toward poverty alleviation and the fulfillment of basic needs. The integration of the AHP–SAW methods thus establishes a systematic and adaptive decision-making framework for determining regional economic development priorities.

C. SAW Results and Development Alternative Priorities

The Simple Additive Weighting (SAW) method is employed to determine the priority of regional economic development alternatives for each regional cluster. Development alternatives for each cluster are defined differently according to the development objectives and economic characteristics identified through the clustering analysis. The criteria weights obtained from the AHP method are used as weighting factors in the SAW process, ensuring that the ranking of development alternatives is contextual and relevant to the conditions of each cluster.

In the SAW stage, the performance values of each alternative across all criteria are normalized according to the type of criteria (benefit or cost) and subsequently multiplied by the corresponding AHP weights. The final preference value is obtained by summing these weighted normalized values and is then used to determine the priority ranking of development alternatives within each cluster.

The development alternatives for each cluster are defined as follows.

Cluster 1. Advanced regions with development objectives focused on acceleration and competitiveness enhancement
Development alternatives:

- A1: Industrial downstreaming
- A2: Digitalization of small and medium-scale enterprises
- A3: Innovation and R&D
- A4: Investment strengthening

Cluster 2. Underdeveloped regions with development objectives focused on equity and basic intervention
Development alternatives:

- B1: Basic infrastructure
- B2: Poverty alleviation
- B3: Labor-intensive programs
- B4: Education and health

Cluster 3. Developing regions with development objectives focused on accelerating economic growth
Development alternatives:

- C1: Strengthening of small and medium-scale enterprises
- C2: Economic infrastructure
- C3: Human resource development
- C4: Leading sector development

The priority alternatives identified for each cluster are subsequently mapped to all regions based on the clustering results, allowing each region to receive development recommendations that are specific and consistent with its regional characteristics. Accordingly, these mapping results can be directly utilized by policymakers as a basis for determining program priorities and allocating resources in regional economic development planning. The best development solution alternatives for each region, as a decision-ready output, are presented in Table 3.

TABLE 3
BEST DEVELOPMENT ALTERNATIVES FOR 38 REGENCIES/MUNICIPALITIES IN EAST JAVA

Regency/Municipality (Cluster)	Priority 1	Priority 2	Priority 3	Priority 4
Pacitan (3)	MSME strengthening	Economic infrastructure	Leading sector development	Human resource development
Ponorogo (3)	MSME strengthening	Human resource development	Economic infrastructure	Leading sector development
Trenggalek (3)	MSME strengthening	Economic infrastructure	Leading sector development	Human resource development
Tulungagung (3)	MSME strengthening	Human resource development	Economic infrastructure	Leading sector development
Blitar (3)	Human resource development	MSME strengthening	Economic infrastructure	Leading sector development
Kediri (3)	Human resource development	Economic infrastructure	Leading sector development	MSME strengthening
Malang (3)	Economic infrastructure	Leading sector development	Human resource development	MSME strengthening
Lumajang (3)	MSME strengthening	Economic infrastructure	Human resource development	Leading sector development
Jember (3)	MSME strengthening	Economic infrastructure	Leading sector development	Human resource development
Banyuwangi (3)	MSME strengthening	Human resource development	Economic infrastructure	Leading sector development
Bondowoso (3)	MSME strengthening	Human resource development	Economic infrastructure	Leading sector development
Situbondo (3)	MSME strengthening	Economic infrastructure	Leading sector development	Human resource development
Probolinggo (3)	MSME strengthening	Economic infrastructure	Leading sector development	Human resource development
Pasuruan (3)	Economic infrastructure	Leading sector development	Human resource development	MSME strengthening
Sidoarjo (1)	Innovation and R&D	Investment strengthening	MSME digitalization	Industrial downstreaming
Mojokerto (3)	Leading sector development	Economic infrastructure	Human resource development	MSME strengthening
Jombang (3)	MSME strengthening	Leading sector development	Economic infrastructure	Human resource development
Nganjuk (3)	MSME strengthening	Human resource development	Economic infrastructure	Leading sector development
Madiun (3)	Human resource development	MSME strengthening	Economic infrastructure	Leading sector development
Magetan (3)	MSME strengthening	Leading sector development	Economic infrastructure	Human resource development
Ngawi (3)	MSME strengthening	Human resource development	Economic infrastructure	Leading sector development
Bojonegoro (2)	Poverty alleviation	Labor-intensive programs	Basic infrastructure	Education and health
Tuban (3)	Human resource development	MSME strengthening	Economic infrastructure	Leading sector development
Lamongan (3)	Human resource development	Leading sector development	Economic infrastructure	MSME strengthening
Gresik (1)	Innovation and R&D	Investment strengthening	MSME digitalization	Industrial downstreaming
Bangkalan (2)	Poverty alleviation	Labor-intensive programs	Basic infrastructure	Education and health
Sampang (2)	Poverty alleviation	Labor-intensive programs	Basic infrastructure	Education and health
Pamekasan (3)	MSME strengthening	Economic infrastructure	Leading sector development	Human resource development

Sumenep (2)	Poverty alleviation	Basic infrastructure	Labor-intensive programs	Education and health
Kediri City (1)	Investment strengthening	Industrial downstreaming	Innovation and R&D	MSME digitalization
Blitar City (1)	Innovation and R&D	Investment strengthening	MSME digitalization	Industrial downstreaming
Malang City (1)	Innovation and R&D	Investment strengthening	Industrial downstreaming	MSME digitalization
Probolinggo City (3)	Human resource development	Leading sector development	Economic infrastructure	MSME strengthening
Pasuruan City (1)	Innovation and R&D	Investment strengthening	MSME digitalization	Industrial downstreaming
Mojokerto City (1)	Innovation and R&D	Investment strengthening	MSME digitalization	Industrial downstreaming
Madiun City (1)	Innovation and R&D	Investment strengthening	Industrial downstreaming	MSME digitalization
Surabaya City (1)	Investment strengthening	Innovation and R&D	Industrial downstreaming	MSME digitalization
Batu City (1)	Investment strengthening	Innovation and R&D	Industrial downstreaming	MSME digitalization

D. Discussion and Policy Implications

The results of regional economic development priority determination demonstrate a strong linkage between regional cluster characteristics, AHP-derived criteria weights, and SAW-based priority development alternatives. This integrated approach enables result interpretation not only at the methodological output level but also within the structural context of economic development across different regional groups.

In the developing region cluster, which is generally characterized by moderate levels of GRDP per capita and HDI alongside relatively high economic growth rates, development priorities are dominated by the strengthening of small and medium-scale enterprises and the development of economic infrastructure. These characteristics indicate that regions within this cluster are in a transitional phase from factor-based economies toward more productive economic structures. The relatively high AHP weights assigned to economic growth and GRDP per capita drive development alternatives aimed at enhancing production capacity and economic connectivity. Strengthening small and medium-scale enterprises becomes the primary priority due to their adaptability in absorbing labor and expanding the local economic base, while economic infrastructure serves as a prerequisite for sustaining growth. Subsequent priorities, such as leading sector development and human resource improvement, reflect the need for developing regions to strengthen their medium-term economic structures.

Conversely, in the advanced region cluster, characterized by high GRDP per capita and HDI values as well as relatively low poverty levels, development priorities shift toward innovation and R&D, investment strengthening, and industrial downstreaming. These characteristics suggest that the main challenges faced by advanced regions are no longer related to economic capacity limitations but rather to value-added creation, productivity enhancement, and competitiveness improvement. High AHP weights for HDI, GRDP per capita, and economic growth directly encourage knowledge- and technology-based development alternatives. The digitalization of small and medium-scale enterprises also emerges as an important complementary strategy, particularly in supporting the integration of local enterprises into modern value chains. This pattern confirms that advanced regions require development strategies oriented toward growth quality and long-term economic sustainability.

Meanwhile, in the underdeveloped region cluster, characterized by high poverty incidence, low HDI, and limited basic infrastructure, development priorities are strongly concentrated on poverty alleviation, labor-intensive programs, and basic infrastructure development. These characteristics indicate that economic challenges in underdeveloped regions remain fundamental and require direct government intervention. Dominant AHP weights assigned to poverty, unemployment, and HDI generate development alternatives focused on fulfilling basic needs and improving community welfare in the short term. Education and health emerge as subsequent priorities, emphasizing the importance of human capital development as a medium-term foundation for escaping structural underdevelopment.

Despite regions belonging to the same cluster, SAW results reveal variations in the priority rankings across regencies and municipalities. This finding indicates that the SAW method effectively captures differences in problem intensity and development potential among regions within the same cluster. Accordingly, the integration of clustering and the hybrid AHP–SAW approach not only produces policy recommendations at the cluster level but also delivers more precise and region-specific recommendations.

Overall, the interaction between cluster characteristics, AHP criteria weights, and SAW ranking results demonstrates that this approach supports evidence-based and differentiated regional economic development decision-making. The findings provide a robust analytical framework for local governments to determine development focus areas, establish program priorities, and allocate resources more effectively in accordance with actual regional conditions.

IV. Conclusion

This study demonstrates that integrating a clustering approach with the hybrid Analytical Hierarchy Process (AHP)–Simple Additive Weighting (SAW) method provides a systematic, contextual, and data-driven decision-making framework for determining regional economic development priorities. The clustering results confirm substantial economic heterogeneity across regions in East Java Province, indicating that uniform development policies are inappropriate. AHP-based criteria weighting reveals different development focuses across clusters, with advanced regions prioritizing competitiveness, human capital quality, and value creation, developing regions emphasizing economic growth acceleration and employment expansion, and underdeveloped regions requiring basic interventions centered on poverty alleviation and welfare improvement. Furthermore, the SAW method produces clear and measurable rankings of development alternatives down to the regency and municipal levels, generating operational and decision-ready policy recommendations. Overall, the clustering and hybrid AHP–SAW framework serves as a transparent and adaptive decision-support tool for more effective, efficient, and equitable regional economic development planning. This study has several limitations, including reliance on secondary data, potential subjectivity in AHP judgments, and the static nature of cross-sectional analysis, which may not fully capture dynamic economic changes.

References

[1] A. A. Anwar, I. P. F. Rorong, and K. D. Tolosang, “Analisis Ketimpangan Pembangunan Antar Wilayah Di Kabupaten/Kota Provinsi Sulawesi Utara,” *J. Berk. Ilm. Efisiensi*, vol. 23, no. 6, pp. 85–96, 2023, [Online]. Available: https://ejournal.unsrat.ac.id/v3/index.php/jbie/article/view/49241.

[2] S. Suparman and M. Muzakir, “Regional Inequality, Human Capital,Unemployment, And Economic Growth in Indonesia: Panel Regression Approach,” *Cogent Econ. Financ.*, vol. 11, no. 2, pp. 1–14, 2023, doi: https://doi.org/10.1080/23322039.2023.2251803.

[3] S. A. A. I. D. Ananda and Y. I. N. Mahaendra, “Determinants Of Economic Growth And Community Welfare In Districts / Cities In Bali Province, Indonesia,” *Eurasia Econ. Bus.*, vol. 4, no. 82, pp. 25–37, 2024, doi: https://doi.org/10.18551/econeurasia.

[4] R. Nopiah, B. Barika, and S. Septriani, “Analysis of Inequality Structure and Its Correlation with Government Expenditure : A Study of Western Indonesia,” *Int. J. Econ. Manag. Account.*, vol. 1, no. 4, pp. 450–468, 2024, doi: https://doi.org/10.61132/ijema.v1i4.295.

[5] S. Rabiah, A. R. Kusuma, S. Rande, and M. Oyekan, “Local Economic Development Based on Regional Potential as a Means of Increasing Community Participation in Tanjung Laut Indah,” *JED J. Etika Demokr.*, vol. 10, no. 4, pp. 582–607, 2025, doi: https://doi.org/10.26618/qpbskb56.

[6] E. G. Asnawi, D. Engka, and E. N. Walewangko, “Analisis Pertumbuhan Ekonomi Inklusif Di Kabupaten Bolaang Mongondow Dan Kota Kotamobagu,” *J. Pembang. Ekon. dan Keuang. Drh.*, vol. 23, no. 3, pp. 19–35, 2022, doi: https://doi.org/10.35794/jpekd.44941.23.3.2022.

[7] A. Diemer, S. Iammarino, A. Rodríguez-Pose, and M. Storper, “The Regional Development Trap in Europe,” *Econ. Geogr.*, vol. 98, no. 5, pp. 487–509, 2022, doi: https://doi.org/10.1080/00130095.2022.2080655.

[8] A. Fitriady, V. Silvia, and S. Suriani, “The Impact of Macroeconomic Variables on the Real Economic Growth in Indonesia,” *Int. J. Glob. Optim. Its Appl.*, vol. 1, no. 2, pp. 70–79, 2022, doi: https://doi.org/10.56225/ijgoia.v1i2.16.

[9] N. Tekman and M. Ordu, “The Rise and Fall of Regions: A Hybrid Multi-Criteria Analysis of Türkiye’s Regional Economies’ Sustainable Performance,” *Sustainability*, vol. 17, no. 11, p. 5222, 2025, doi: https://doi.org/10.3390/su17115222.

[10] F. O. Olokoyo, O. W. Ibhagui, and A. Babajide, “Macroeconomic indicators and capital market performance: Are the links sustainable?,” *Cogent Bus. Manag.*, vol. 7, no. 1, 2020, doi: https://doi.org/10.1080/23311975.2020.1792258.

[11] C. R. Ohakwe and J. Wu, “The impact of macroeconomic indicators on logistics performance: A comparative analysis using simulated scenarios,” *Sustain. Futur.*, vol. 9, 2025, doi: https://doi.org/10.1016/j.sftr.2025.100567.

[12] R. Ramadhani and N. Hasanah, “Perekonomian Indonesia Khususnya Pada Tingkat Makro,” *Mutiara J. Penelit. dan Karya Ilm.*, vol. 2, no. 2, pp. 280–286, 2024, doi: https://doi.org/10.59059/mutiara.v2i2.1147.

[13] Hasbiullah, M. Febriansyah, B. Iwang, and V. N. S. Rasyid, “The Impact of Unemployment, Human Development Index and Internet Penetration on Income Inequality: Evidence from the Sulawesi Region, Indonesia,” *Sriwij. Int. J. Dyn. Econ. Bus.*, vol. 9, no. 4, pp. 337–350, 2025, doi: https://doi.org/10.29259/sijdeb.v9i4.337-350.

[14] R. A. Yusnuri and J. Abubakar, “Analysis Of Human Development Index, Unemployment And Poverty On Economic Growth In Indonesia,” *Int. J. Soc. Sci. Educ. Econ. Agric. Res. Technol.*, vol. 2, no. 8, pp. 346–358, 2023, doi: https://doi.org/10.54443/ijset.v2i8.190.

[15] C. Anwari and A. Ambariyanto, “Dampak Pertumbuhan Ekonomi, Indeks Pembangunan Manusia Dan Tingkat Pengangguran Terbuka Terhadap Kemiskinan Di Kawasan Jabodetabek,” *NEOBIS J. Berk. Ilmu Ekon.*, vol. 13, no. 2, pp. 204–218, 2024, doi: https://doi.org/10.21107/nbs.v13i2.28904.

[16] A. J.Lala, A. T. Naukoko, and H. F. D. Siwu, “Analisis Pengaruh Pertumbuhan Ekonomi Dan Indekspembangunan Manusia Terhadap Tingkatketimpanganpendapatan(Studi Pada Kota –Kota Di Provinsi Sulawesi Utara),” *J. Berk. Ilm. Efisiensi*, vol. 23, no. 1, pp. 61–72, 2023, [Online]. Available: https://ejournal.unsrat.ac.id/v3/index.php/jbie/article/view/45150/40820.

[17] C. Saraiva and J. Caiado, “Global development patterns: A clustering analysis of economic, social and environmental indicators,” *Sustain. Futur.*, vol. 10, 2025, doi: https://doi.org/10.1016/j.sftr.2025.100907.

[18] P. Rezabek, L. Marek, P. Doucek, and L. Nedomova, “A Comparison of the Development of Selected Macroeconomic Indicators of the Regions of the V4 Countries,” *Qual. Innov. Prosper.*, vol. 26, no. 2, pp. 21–38, 2022, doi: https://doi.org/10.12776/QIP.V26I2.1695.

[19] R. I. Urzais and W. Rachbini, “Analisis K-Means Cluster Untuk Pengelompokan Wilayah Jawa Barat Berdasarkan Besaran Apbd Dan Pendapatan Per Kapita,” *Gt. Glob. Res. Innov. J.*, vol. 1, no. 3, pp. 2925–2938, 2025.

[20] A. E. P. Haryanto and M. U. Yanuar, “Metode K-Means Clustering untuk Pengelompokan Kabupaten/Kota dalam Upaya Pengendalian Tingkat Inflasi di Pulau Jawa dan Sumatera,” *Goverment Stat.*, vol. 1, no. 1, pp. 29–42, 2022.

[21] A. M. Kowalski and M. Mackiewicz, “Commonalities and Differences of Cluster Policy of Asian Countries; Discussion on Cluster Open Innovation,” *J. Open Innov. Technol. Mark. Complex.*, vol. 7, no. 1, p. 21, 2021, doi: https://doi.org/10.3390/joitmc7010021.

[22] M. D. Salman *et al.*, “Comparison of K-Means and K-Medoids Clustering Algorithm Performance in Grouping Schools in Riau Province Based on Availability of Facilities and Infrastructure,”

MALCOM Indones. J. Mach. Learn. Comput. Sci., vol. 5, no. 3, pp. 797–806, 2025, doi: https://doi.org/10.57152/malcom.v5i3.1950.

[23] S. Supriyadi and A. G. Malau, "Clustering dengan Menggunakan K-Means untuk Analisa Dampak Banjir," *J. Impresi Indones.*, vol. 4, no. 9, pp. 3428–3436, 2025, doi: https://doi.org/10.58344/jii.v4i9.6998.

[24] R. H. Bhahari and Kusnawi, "Clustering Analysis of Socio-Economic Districts/Cities In East Java Province Using PCA And Hierarchical Clustering Methods," *Sink. J. dan Penelit. Tek. Inform.*, vol. 8, no. 4, pp. 2242–2251, 2024, doi: https://doi.org/10.33395/sinkron.v8i4.14078.

[25] T. A. Munandar and D. Handayani, "K-Means Cluster Algorithm for Grouping Inequality in Regional Development," *Int. J. Inf. Technol. Comput. Sci. Appl.*, vol. 1, no. 1, pp. 66–70, 2023, doi: https://doi.org/10.58776/ijitcsa.v1i1.20.

[26] T. E. Siregar and E. S. M. Nababan, "Analisis Keputusan Dalam Menentukan Penerima Bantuan Lansung Tunai Dana Desa Menggunakan Metode Analytical Hierarchy Process," *FARABI J. Mat. dan Pendidik. Mat.*, vol. 5, no. 2, pp. 199 – 207, 2022, doi: https://doi.org/10.47662/farabi.v5i2.419.

[27] L. Laurentinus, "Penerapan Metode AHP dan SAW untuk Rekomendasi Keluarga Kurang Mampu Penerima Bantuan," *J. Teknol. Inf. dan Terap.*, vol. 9, no. 1, pp. 62–69, 2022, doi: https://doi.org/10.25047/jtit.v9i1.275.

[28] F. A. Tanti, G. W. Wicaksono, and A. E. Minarno, "Sistem Pendukung Keputusan Prioritas Lokasi Perbaikan Jalan Menggunakan Metode Analyical Hierarchy Process dan Simple Additive Weighting Studi Kasus Kabupaten Pasuruan," *REPOSITOR*, vol. 2, no. 9, pp. 1249–1256, 2020, doi: https://doi.org/10.22219/repositor.v2i9.1004.

[29] N. Indriyani, A. Fauzi, and A. B. H. Yanto, "A Decision-Making Model for Kindergarten School Selection Using the AHP Method: A Case Study of West Bekasi," *J. Teknol. DAN OPEN SOURCE*, vol. 8, no. 2, pp. 1232–1242, 2025, doi: https://doi.org/10.36378/jtos.v8i2.5096.

[30] D. Kurniawati, F. N. Lenti, and R. W. Nugroho, "Implementation of AHP and SAW Methods for Optimization of Decision Recommendations," *JICP J. Int. Conf. Proc.*, vol. 4, no. 1, pp. 254–265, 2021, doi: https://doi.org/10.32535/jicp.v4i1.1152.

[31] S. S. Rakhmawati, "Implementasi Metode Analytical Hierarchy Process (AHP) Dalam Sistem Pendukung Keputusan Kelayakan Pengajuan KPR Subsidi Di PT. Indragriya Putera," *RIGGS J. Artif. Intellegence Digit. Bus.*, vol. 4, no. 3, pp. 4797–4803, 2025.

[32] Q. F. F. Safiesza, L. M. Sari, M. Yogi, A. A. Sunarya, M. N. Farras, and M. F. Evizal, "Using Analytic Hierarchy Process (AHP) and Fuzzy Analytic Hierarchy Process (F-AHP) Methods in Criteria and Alternative Perspectives for Ranking," *IJATIS Indones. J. Appl. Technol. Innov. Sci.*, vol. 1, no. 2, pp. 61–67, 2024, doi: https://doi.org/10.57152/ijatis.v1i2.1137.

[33] L. V. Cremades and A. Ponsich, "Simple and objective determination of criteria weights for evaluating alternatives when using the Analytic Hierarchy Process," *Int. J. Anal. Hierarchy Process*, vol. 16, no. 3, pp. 1–23, 2024, doi: https://doi.org/10.13033/ijahp.v16i3.1177.

[34] I. Zakaria, G. I. Marthasari, and I. Nuryasin, "Penerapan Metode Simple Additive Weighting (Saw) Pada Sistem Pendukung Keputusan Pemilihan Bidang Minat Oleh Mahasiswa (Studi Kasus : Prodi Informatika Umm)," *JATI J. Mhs. Tek. Inform.*, vol. 9, no. 3, pp. 5267–5274, 2025, doi: https://doi.org/10.36040/jati.v9i3.13737.

[35] S. Wulandari and A. P. Wibowo, "Development of SAW (Simple Additive Weighting) Method for Decision Support System of Sembako Price Control (Case Study of the Office of Agriculture, Fisheries and Forestry, Sleman Regional Government)," *Int. J. Eng. Technol. Nat. Sci.*, vol. 1, no. 1, pp. 34–41, 2019, doi: https://doi.org/10.46923/ijets.v1i1.23.

[36] E. Naibaho, "Application of the SAW Method in the Decision Support System for Employee Performance Assessment at PT. Sarma Amarise Anugerah Sejahtera," *JATILIMA J. Multimed. Dan Teknol. Inf.*, vol. 6, no. 3, pp. 54–59, 2024, doi: https://doi.org/10.54209/jatilima.v6i03.1186.

[37] A. P. Widyassari, M. A. An'syah, and R. Wahyusari, "Comparative Analysis Of Saw And Topsis In Selecting Recipients Of Basic Food Assistance," *ICTMT*, vol. 1, no. 1, pp. 174-183, 2023. doi: https://doi.org/10.56910/ictmt.v1i1.61.

[38] F. Ciardiello and A. Genovese, "A comparison between TOPSIS and SAW method", *Ann. of Opr. Res*., vol. 325, pp. 967-994, 2023. doi: https://doi.org/10.1007/s10479-023-05339-w.

[39]

[40] A. Fahriza, S. A. Putri, and T. Zebua, "Penerapan Metode MOORA dalam Sistem Pendukung Keputusan Menentukan Prioritas Proyek Pembangunan Infrastruktur," *JATILIMA J. Multimed. Dan Teknol. Inf.*, vol. 7, no. 4, pp. 973–984, 2026, doi: https://doi.org/10.54209/jatilima.v7i04.1939.

[41] I. M. Usman, R. W. Sayekti, and S. Wahyuni, "Penentuan Prioritas Rencana Pengelolaan Kinerja Irigasi di Wilayah Sungai Pekalen Sampean dengan Menggunakan Metode Multiple Attribute Decision Making (MADM)," *J. Teknol. dan Rekayasa Sumber Daya Air*, vol. 6, no. 1, pp. 250–259, 2026, doi: https://doi.org/10.21776/ub.jtresda.2026.6.1.24.

[42] K. He, B. Huang, X. Liu, and S. Zeng, "Assessment of economic development of central business districts – A combination multi-criteria evaluation methodology," *PLoS One*, vol. 20, no. 7, 2025, doi: https://doi.org/10.1371/journal.pone.0326877.

[43] V. A. Fitria and Y. A. Sapoetra, "Implementasi Metode SAW untuk Mengetahui Kondisi Perekonomian Kabupaten/Kota di Provinsi Jawa Timur," *J. Ilm. Teknol. Inf. Asia*, vol. 16, no. 2, pp. 133–138, 2022, doi: https://doi.org/10.32815/jitika.v16i2.769.

[44] M. A. Umar, S. Surorejo, and P. S. Ananda, "Penerapan Metode SAW dalam Sistem Pendukung Keputusan pada Pemberian Bantuan Pedagang Pasar," *Tek. J. ILMU Tek. DAN Inform.*, vol. 2, no. 2, pp. 67–76, 2022, doi: https://doi.org/10.51903/teknik.v2i3.159.

[45] B. E. Waruwu and A. Simangunsong, "Application of the Simple Additive Weighting (SAW) Method in Determining The Best Customers for Home Furniture," *LOGIN J. Teknol. Komput.*, vol. 14, no. 2, pp. 315–321, 2020.

[46] Badan Pusat Statistik Provinsi Jawa Timur, "Provinsi Jawa Timur Dalam Angka 2025." [Online]. Available: https://jatim.bps.go.id/id/publication/2025/02/28/5ae8b994b1bebd8cbc2e0781/provinsi-jawa-timur-dalam-angka-2025.html

[47] Badan Pusat Statistik Provinsi Jawa Timur, "Statistik Daerah Provinsi Jawa Timur 2025." [Online]. Available: https://jatim.bps.go.id/id/publication/2025/09/26/2bab13295c7644f4f808694c/statistik-daerah-provinsi-jawa-timur-2025.html

[48] A. D. Rohma and E. Hariani, "Effect of Wages, Economic Growth, and Human Development Index on the Labor Force Participation Rate", *Airlangga J. of Inv. Mgmnt*., vol. 6, no. 4, 2025. doi: https://doi.org/10.20473/ajim.v6i4.75567.

[49] M. A. Falah and F. Rahmawati, "The GRDP per capita, human development index, open unemployment rate, regional expenditure, and poverty in East Java Province",*JESP*, vol. 21, n0. 1, pp. 1-16, 2024. Doi: https://doi.org/10.18196/jesp.v25i1.21327.

[50] I. G. A. U. Giri and H. P. M. Dewa, "Implementation of the Simple Additive Weighting (SAW) Method in a Decision Support System for Tourist Destination Selection in North Bali", JSIKTI, vol. 6, no. 1, 2023. Doi: https://doi.org/10.33173/jsikti.261.

[51] M. I. Albani and Hutapia, "The influence of the Human Development Index (HDI), GDP Per Capita and Open Unemployment Rate to Poverty in Regencies/Cities of Aceh Province in 2017 – 2022", Asian J. of Manag. Anal., vol. 4, no. 1, pp. 419-434, 2025. doi: https://doi.org/10.55927/ajma.v4i1.13779.

[52] G. P. Jafba and R. Juanda, "Influence Of Gross Regional Domestic Product And Open Unemployment Rate On The Human Development Indeks In Lampung Province For The Years 2017-2021", JOMPE, vol. 6, no. 2, pp. 9-19, 2023. doi: https://doi.org/10.29103/jompe.v6i2.13753.

[53] M. Sinaga, "Analysis of Effect of GRDP (Gross Regional Domestic Product) Per Capita, Inequality Distribution Income, Unemployment and HDI (Human Development Index) on Poverty", *Budapest Int. Res. And Crit. Inst.*, vol. 3, no. 3, pp. 2309-2318, 2020. Doi: https://doi.org/10.33258/birci.v3i3.1177.

[54] P. N. Alifah and Z. Arifin, "Analysis The Influence of Per Capita GRDP, Poverty, Income Inequality, and Open Unemployment Rate on

the Inclusive Economic Development Index in Kalimantan Island", JIE: J. Ilmu Ekon., vol. 9, no. 1, pp. 57-66, 2025. doi: https://doi.org/10.22219/jie.v9i01.32842.

[55] S. Amalia *et al.*, "Implementasi Algoritma K-Means Clustering Dalam Pemetaan Kondisi Perpustakaan Di Indonesia Berdasarkan Provinsi Tahun 2023," *JATI J. Mhs. Tek. Inform.*, vol. 9, no. 4, pp. 6252–6259, 2025.

[56] M. Darwis, L. H. Hasibuan, M. Firmansyah, N. Ahady, and R. Tiaharyadini, "Implementation of K-Means clustering algorithm in mapping the groups of graduated or dropped-out students in the Management Department of the National University," *JISA J. Inform. dan Sains*, vol. 4, no. 1, pp. 1–9, 2021, doi: https://doi.org/10.31326/jisa.v4i1.848.

[57] P. P. Pane, Y. R. Nasution, and M. Furqan, "Implementasi Data Mining dengan K-Means Clustering untuk Memprediksi Pengadaan Obat," *J. Comput. Syst. Informatics*, vol. 5, no. 2, pp. 286–296, 2024, [Online]. Available: https://doi.org/10.47065/josyc.v5i2.4920

[58] M. Alvarez-Garcia, R. Ibar-Alonso, and M. Arenas-Parra, "A comprehensive framework for explainable cluster analysis," *Inf. Sci. (Ny).*, vol. 663, 2024, doi: https://doi.org/10.1016/j.ins.2024.120282.

[59] A. L. Nogueira, "The effect of data standardization in cluster analysis," *Brazilian J. Radiat. Sci.*, vol. 9, no. 1, pp. 1–15, 2021, doi: https://doi.org/10.15392/bjrs.v9i1A.1324.

[60] I. Prastika and D. P. Sari, "Hierarchical Clustering of Education Indicators in Papua Island: A Ward's Method Approach," *JAIC J. Appl. Informatics Comput.*, vol. 9, no. 4, pp. 1544–1550, 2025, doi: https://doi.org/10.30871/jaic.v9i4.9740.

[61] T. Apriliana and E. Widodo, "Analisis Cluster Hierarki untuk Pengelompokan Provinsi di Indonesia berdasarkan Jumlah Base Transceiver Station dan Kekuatan Sinyal," *J. Konstelasi*, vol. 3, no. 2, pp. 286–296, 2023, doi: https://doi.org/10.24002/konstelasi.v3i2.7143.

[62] A. Patandianan, A. Irsyad, and M. R. Ibrahim, "Penerapan Algoritma K-Means Clustering Dalam Pengelompokan Produksi Padi Di Provinsi Kalimantan Timur," *JATI J. Mhs. Tek. Inform.*, vol. 9, no. 5, pp. 7443–7452, 2025, doi: https://doi.org/10.36040/jati.v9i5.14651.

[63] I. W. Napitupulu, C. V. Sinaga, A. Rahman, and M. N. Steven, "Application Of The K-Means Clustering Method For Performance Assessment Based On The Competency Ofeducators," *J. Sist. Inf. dan Ilmu Komput. Prima*, vol. 7, no. 1, pp. 50–60, 2023, doi: https://doi.org/10.34012/jurnalsisteminformasidanilmukomputer.v7i1.3951.

[64] A. Rolidani, F. Riana, and G. F. Laxmi, "Implementasi Metode Hybrid Pada Sistem Pendukung Keputusan Untuk Menentukan Toko Yang Layak Mendapatkan Suplai Barang (Studi Kasus: Ar JeanS)," *JATI J. Mhs. Tek. Inform.*, vol. 8, no. 3, pp. 2672–2679, 2024, doi: https://doi.org/10.36040/jati.v8i3.9546.