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REGIONAL GROUPING AND HUMAN DEVELOPMENT INEQUALITY IN WEST NUSA TENGGARA: AN EMPIRICAL STUDY USING HIERARCHICAL CLUSTER AND DAVIES BOULDIN INDEX

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Abstract

This study analyzes the spatial grouping of cities and districts in West Nusa Tenggara (NTB), Indonesia, based on indicators of the Human Development Index (HDI). Using secondary data from the NTB Central Bureau of Statistics for 2022, four HDI components, which include life expectancy at birth, expected years of schooling, mean years of schooling, and adjusted per capita expenditure, were employed as clustering variables. A hierarchical cluster analysis with various linkage methods, including average, single, complete, centroid, median, and Ward methods, was applied to classify the ten cities and districts. The optimal number of clusters was determined using the Davies–Bouldin Index (DBI). The results reveal that the lowest DBI value (0.4573) was obtained through the single linkage method, indicating the formation of three optimal clusters. The first cluster includes West Lombok and West Sumbawa Regencies, the second cluster consists of Central Lombok, East Lombok, Sumbawa, Dompu, Bima, North Lombok, and Bima City, while the third cluster contains only Mataram City. The findings highlight regional disparities in HDI performance across NTB and suggest that human development programs should be tailored according to the characteristics of each cluster to ensure more equitable progress among regions.

KEYWORDS: Human Development Index, cluster analysis, regional disparities, West Nusa Tenggara, hierarchical clustering.

1. INTRODUCTION

Human development lies at the core of the sustainable development process. The success of development can no longer be measured solely by economic growth, but rather by the extent to which it improves the overall quality of human life (UNDP, 2023). In the modern paradigm of development, people are viewed not merely as objects of policy, but as active agents who determine the direction, pace, and outcomes of social, economic, and cultural transformation (UNDP, 2021). This understanding emphasizes that genuine development is achieved when economic progress translates into greater opportunities and freedoms for people to live long, healthy, and meaningful lives.

The concept of Human Development gained global recognition when it was introduced by the United Nations Development Programme (UNDP) through the inaugural *Human Development Report* published in 1990, which presented the Human Development Index (HDI) as a composite measure of development achievements across three fundamental dimensions: a long and healthy life, knowledge, and a decent standard of living. According to the latest HDI technical framework, these dimensions are measured using life expectancy at birth to represent health; expected years of schooling and mean years of schooling to represent education; and Gross National Income (GNI) per capita adjusted for purchasing power parity (PPP US$) to represent the standard of living (UNDP, 2024).

The introduction of the HDI marked a paradigm shift from an economy centered to a human centered approach in development assessment. Prior to its adoption, development success was predominantly evaluated based on macroeconomic indicators such as Gross Domestic Product (GDP). However, an expanding body of research has shown that increases in national income do not necessarily reflect improvements in human well being (UNDP, 2021). Thus, the HDI provides a more holistic framework that integrates health, education, and income dimensions as interdependent and complementary measures of progress. In Indonesia, however, the Central Bureau of Statistics (BPS) adjusts the income dimension by using adjusted per capita expenditure instead of GNI per capita, reflecting national socioeconomic characteristics and data availability (BPS, 2024).

In Indonesia, the Human Development Index has been officially adopted as one of the principal macro indicators for monitoring and evaluating the quality of life of the population. The Central Bureau of Statistics (Badan Pusat Statistik or BPS) calculates the HDI annually for all provinces and districts by referring to the UNDP measurement framework while incorporating methodological adjustments that reflect Indonesia's socio-economic conditions (BPS, 2023). In the Indonesian context, the HDI is constructed using four main variables, namely life expectancy at birth, expected years of schooling, mean years of schooling, and adjusted per capita expenditure, which serve as statistical representations of the health, education, and standard-of-living dimensions of human development (BPS, 2023).

Over the past decade, Indonesia has made steady progress in human development. According to BPS data, the national HDI rose from 68.90 in 2014 to 74.39 in 2023 (BPS, 2023). Although growth slowed temporarily in 2020 due to the impacts of the COVID 19 pandemic, which disrupted education and household incomes, recovery was swift in the following years. This steady improvement reflects the government's continued commitment to human capital investment through health services, education access, and poverty alleviation programs (BPS, 2023).

However, the aggregate national improvement conceals persistent regional disparities. HDI levels vary widely between provinces and districts, with western Indonesia (notably Java and parts of Sumatra) recording higher values, while eastern Indonesia including Nusa Tenggara, Maluku, and Papua continues to lag behind. These disparities stem from differences in infrastructure quality, population density, industrialization, and local fiscal capacity (BPS, 2022). Addressing these imbalances remains one of Indonesia's foremost policy challenges in realizing equitable and inclusive development.

Among the regions with relatively low HDI performance is West Nusa Tenggara (NTB), a province consisting of the islands of Lombok and Sumbawa, each with distinct socio economic and demographic characteristics. According to BPS (2023), NTB's HDI stood at 70.20, placing it among the six lowest provinces in Indonesia (BPS, 2023). This figure indicates that the overall human development outcomes in NTB remain below the national average and that significant disparities exist within the province itself.

Data from BPS (2022) show that the average expected years of schooling in NTB is 13.95 years, the mean years of schooling is 8.04 years, adjusted per capita expenditure amounts to 10,751.54 thousand rupiah per person per year, and life expectancy at birth averages 68.17 years (BPS, 2022). Although these figures suggest moderate improvement compared to previous years, the intra provincial variations are still considerable. Urban centers such as Mataram City, with better infrastructure and economic diversity, tend to record higher HDI indicators, while rural and agrarian districts such as North Lombok and Bima remain relatively underdeveloped.

Such disparities reveal deep structural and spatial inequalities in human development. Regions with diversified economies and robust access to public services enjoy more rapid human development, whereas areas dependent on subsistence agriculture and limited education systems lag behind. Factors such as infrastructure quality, fiscal capacity, and administrative competence significantly affect the local government's ability to implement effective development policies. Consequently, uneven governance capacity across districts contributes to the persistence of inequality in NTB.

The provincial government of NTB has undertaken numerous programs to improve human development outcomes, including expanding educational opportunities, upgrading health facilities, and empowering local communities through agriculture, fisheries, and tourism initiatives. Nevertheless, these efforts have yet to yield balanced progress across all districts and cities. This situation underscores the need for

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data driven and context sensitive policy approaches that consider the unique socio economic conditions of each region.

To better understand the variation in human development across regions, a more analytical approach is required one that can systematically identify patterns of similarity and difference among districts. Conventional descriptive analyses are often insufficient to capture the multidimensional relationships and interdependencies within regional data. In this regard, cluster analysis offers a statistically sound method for classifying regions according to shared characteristics (Kassambara, 2017). In human development studies, cluster analysis enables researchers to group districts and cities with similar HDI indicators, thereby facilitating a clearer understanding of regional disparities and aiding in the formulation of tailored policy responses.

Among various clustering techniques, hierarchical cluster analysis is particularly suitable for regional classification because it can reveal interregional relationships visually through dendrograms that depict the progressive merging of regions based on similarity (Hennig et al., 2016). This step by step process allows researchers to identify structural relationships and similarities among regions according to multiple dimensions simultaneously.

An essential component of cluster analysis is determining the optimal number of clusters and assessing the validity of the classification. The Davies–Bouldin Index (DBI), developed by Davies and Bouldin (1979), is widely used for this purpose. The DBI evaluates the ratio between intra cluster cohesion and inter cluster separation, where a lower index value indicates more distinct and compact clusters (Davies & Bouldin, 1979). This method ensures that regional classification is based on objective statistical criteria rather than arbitrary assumptions.

Applying such a data driven framework to human development analysis provides practical benefits for policy design. By identifying groups of regions that share similar development characteristics, policymakers can design interventions tailored to the specific needs of each cluster. Analyzing human development using a cluster based approach serves both theoretical and practical purposes. Theoretically, it enhances empirical understanding of regional similarity and diversity in human development. Practically, it provides policymakers with a scientific basis for designing targeted, fair, and context specific development strategies. Achieving inclusive and sustainable human development requires not only economic growth but also policies that are adaptive to regional characteristics. Through hierarchical cluster analysis, it becomes possible to identify underlying patterns of inequality and to design strategic interventions that ensure all regions including those in West Nusa Tenggara have equal opportunities to achieve a higher quality of life.

2. METHOD

This research employs a quantitative approach, drawing entirely on secondary data published by the Central Bureau of Statistics (Badan Pusat Statistik or BPS) of West Nusa Tenggara Province. The analysis focuses on data for the year 2022, covering all ten administrative areas in the provinceWest Lombok, Central Lombok, East Lombok, North Lombok, West Sumbawa, Sumbawa, Dompu, Bima Regency, Bima City, and Mataram City.

Four variables were employed to represent the three key dimensions of human development, namely health, education, and standard of living. These are (1) expected years of schooling, which measures the number of years a child entering school is expected to spend in formal education as X1, (2) mean years of schooling, reflecting the average completed education among adults aged 25 years and above as X2, (3) adjusted per capita expenditure, serving as a proxy for income and living standards as X3, and (4) life expectancy at birth, representing the health dimension as X4.

The main analytical technique used in this study is cluster analysis, a statistical method designed to group objects that share similar characteristics. The technique is widely recognized in social and regional development research for its ability to identify hidden structures and relationships within multidimensional data (Hennig et al., 2016). In this context, cluster analysis is used to classify the ten cities and districts in NTB into relatively homogeneous groups based on their HDI indicator profiles. This approach does not seek to test hypotheses, but rather to explore underlying patterns that reveal how human development differs or converges across regions.

Among the various clustering techniques available, this research applies the hierarchical agglomerative method, a procedure that starts by considering each observation as its own cluster and then successively merges pairs of clusters according to their degree of similarity until a single overarching cluster is formed (Hennig et al., 2016). To provide a comprehensive understanding of the data structure, several linkage algorithms were appliednamely single linkage (nearest neighbor), complete linkage (farthest neighbor), average linkage (between and within groups), centroid linkage, median linkage, and Ward's linkage. Each linkage criterion defines the distance between clusters differently, resulting in variations in the way clusters are formed. The comparison among these methods allows for greater reliability and validity in determining the most consistent clustering pattern (Kassambara, 2017).

To measure the similarity between observations, the Euclidean distance was used as the primary distance metric. The Euclidean distance represents the straight line distance between two objects in multidimensional space and is the most widely used measure of dissimilarity in cluster analysis. The formula is expressed as:

$$d_{ij} = \sqrt{\sum_{k=1}^{n} \left(x_{ik} - x_{jk}\right)^2}$$

where $x_{ik}$and x_{jk}denote the standardized values of variable $k$for objects $i$and j, respectively, and $p$is the total number of variables (Hennig et al., 2016: 42). A smaller distance indicates higher similarity between two regions in terms of their HDI indicators, while a larger distance indicates greater dissimilarity.

3. RESULT AND DISCUSSION

The results of this study indicate that human development across the ten cities and districts of West Nusa Tenggara (NTB) Province remains highly varied and spatially uneven. The analysis was conducted using four key Human Development Index (HDI) indicators, which are expected years of schooling, mean years of schooling, adjusted per capita expenditure, and life expectancy at birth. Based on data published by the Badan Pusat Statistik (BPS) in 2022, the provincial average for expected years of schooling was 13.95 years, while the mean years of schooling reached 8.04 years. The adjusted per capita expenditure was 10,751.54 thousand rupiah per person per year, and life expectancy at birth was 68.17 years. These figures show a general improvement compared with previous years and at the same time highlight significant differences among regions. Urban areas, particularly Mataram City, recorded values that were significantly higher than the provincial average, whereas rural districts such as North Lombok and Dompu exhibited considerably lower outcomes.

A closer examination of the HDI components shows that Mataram City achieved the highest performance in most dimensions. Its expected years of schooling reached 15.65 years, adjusted per capita expenditure was 15,416 thousand rupiah per person per year, and life expectancy was 72.20 years, demonstrating its position as the province's human development center. Meanwhile, Bima City recorded the highest mean years of schooling (10.94 years), reflecting relatively good educational attainment among its adult population. Conversely, North Lombok exhibited the lowest levels of educational attainment with an expected years of schooling of 12.77 years and a mean years of schooling of only 6.30 years. East Lombok had the lowest life expectancy at 66.55 years, which may reflect limited access to healthcare and socio economic facilities. Table 1 summarizes these disparities by listing the highest and lowest values for each HDI indicator in 2022.

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Table 1. Regencies/Cities with the Highest and Lowest Variable Values

The Highest		**Variable**	**The Lowest**	
Regency/City	**Value**		**Regency/City**	**Value**
Mataram	15,65	X1	North Lombok Regency	12,77
Mataram	15416	X2	Bima Regency	8699
Bima City	10,94	X3	North Lombok Regency	6,3
Mataram	72,2	X4	East Lombok Regency	66,55

The differences displayed in Table 1 confirm that spatial inequality in NTB remains pronounced. Urban centers tend to enjoy better education and income indicators, while peripheral rural regions lag behind. This pattern suggests that human development progress is still closely tied to economic concentration and accessibility to social services. To explore these disparities further, a hierarchical agglomerative cluster analysis was applied to the standardized HDI indicators of all ten regions. This method was chosen to group cities and districts according to their degree of similarity in human development outcomes.

The analysis began with the calculation of a Euclidean distance matrix, which measured the level of similarity among regions. The smaller the distance, the more similar the regions are in terms of their HDI indicators. Based on this matrix, hierarchical clustering was performed using six different linkage algorithms that is single, complete, average (between and within groups), centroid, median, and Ward's linkage methods. Among these, the single linkage method was found to produce the most interpretable structure, showing the gradual merging of regions based on their HDI similarities. The dendrogram generated through this method demonstrated that West Lombok and West Sumbawa were the first to merge, signifying close similarities in their socio economic and educational characteristics. This was followed by the grouping of Central Lombok, East Lombok, Sumbawa, Dompu, Bima Regency, North Lombok, and Bima City into a larger cluster, indicating shared development challenges. Mataram City, on the other hand, remained isolated until the last stage of clustering, highlighting its distinctive HDI profile compared to other regions. When compared with the dendrogram produced by the complete linkage method, the general grouping remained consistent, though the latter yielded denser linkages between mid performing regions. These visual patterns collectively suggest that NTB's human development landscape is hierarchically structured with clear urban dominance. The dendrograms generated using the single linkage method and the complete linkage method can be seen in the figure 1. Then the DBI values for each linkage method are presented in Table 2.

Table 2. Davies–Bouldin Index (DBI) for Each Clustering Method

NO	**Number of Clusters**	**DBI**	**Method**
1	3 clusters	1,07203569	Average Linkage Between Groups
	4 clusters	0,7634709	
	5 cluster	0,6429714	
2	3 clusters	0,4573142	Single Linkage
	4 clusters	1,62806899	
	5 cluster	0,6429714	
3	3 clusters	1,07203569	Complete Linkage
	4 clusters	0,7634709	
	5 cluster	0,6429714	
4	3 clusters	1,04877608	Average Linkage Within Groups
	4 clusters	1,62806899	
	5 cluster	0,6429714	
5	3 clusters	1,07203569	Centroid Linkage
	4 clusters	0,7634709	
	5 cluster	0,6429714	
6	3 clusters	1,07203569	Median Linkage
	4 clusters	0,7634709	
	5 cluster	0,6429714	
7	3 clusters	1,07203569	Wards Linkage
	4 clusters	0,7634709	
	5 cluster	0,6429714	

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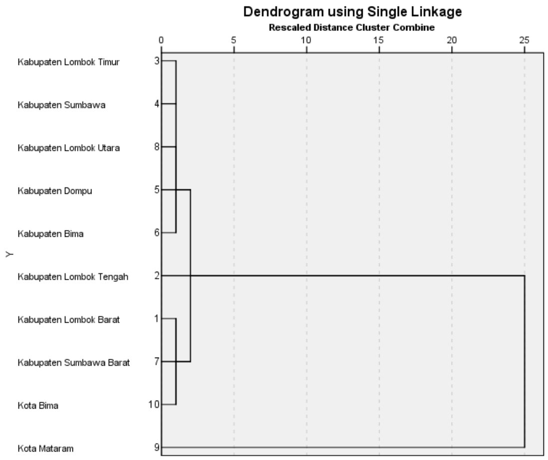
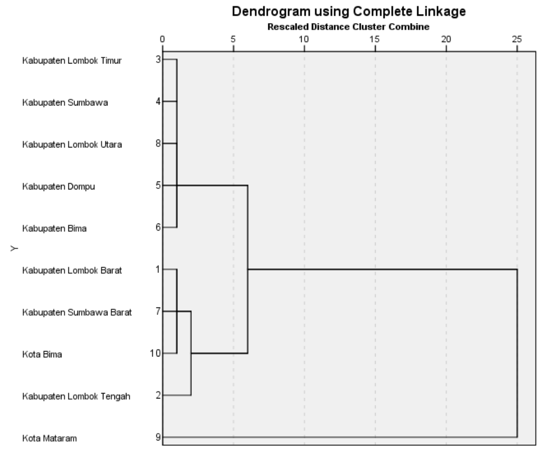


(A) DENDROGRAM USING THE SINGLE LINKAGE



(B) DENDROGRAM USING THE COMPLETE LINKAGE

Figure 1. The Generated Dendrogram

To determine the optimal number of clusters, the validity of each clustering configuration was tested using the Davies–Bouldin Index (DBI), which evaluates the ratio of intra cluster cohesion to inter cluster separation. A smaller DBI value indicates a better clustering structure, with more compact and well separated clusters.

As shown in Table 2, the single linkage method yields the lowest DBI value of 0.4573, signifying that the three cluster configuration provides the most statistically valid structure. Consequently, the ten cities and districts in NTB were classified into three clusters as shown in Table 3.

Table 3. Resulting Clusters

Cluster	Number of Cluster Members	Cluster Members
Cluster 1	2 Regencies	West Lombok, West Sumbawa.
Cluster 2	7 Regencies/Cities	Central Lombok, East Lombok, Sumbawa, Dompu, Bima Regency, North Lombok, Bima City.
Cluster 3	1 City	Mataram

The clustering results indicate three distinct categories of human development in NTB. The first cluster, consisting of West Lombok and West Sumbawa, represents regions with moderate HDI levels. These areas show relatively good economic and health outcomes but still lag behind Mataram City in educational achievement. The second cluster, which encompasses most of the districts that is Central Lombok, East Lombok, Sumbawa, Dompu, Bima Regency, North Lombok, and Bima City represents regions with low HDI levels, characterized by limited access to education, lower per capita income, and shorter life expectancy. The third cluster contains only Mataram City, which clearly stands out as the province's human development hub, with HDI components significantly exceeding both provincial and national averages.

Spatially, the distribution of these clusters forms a clear gradient from west to east. Mataram City, located in the western part of Lombok Island, constitutes a high HDI cluster, surrounded by moderately developed regions such as West Lombok and West Sumbawa. In contrast, the central and eastern parts of NTB, encompassing most of Sumbawa Island, form a broad low HDI cluster. This geographic pattern highlights the persistence of an urban–rural development divide, which is consistent with UNDP findings that economic centralization and urbanization are major drivers of human development inequality across Indonesia (UNDP, 2023).

Quantitatively, the disparity between the highest and lowest HDI indicators further illustrates the depth of inequality. The difference in expected years of schooling between Mataram City and North Lombok Regency is 2.88 years, while the gap in adjusted per capita expenditure exceeds 6.7 million rupiah per year. Similarly, life expectancy differs by 5.65 years between Mataram City and East Lombok Regency. These differences substantiate the cluster distinctions identified in the analysis, showing that the region's human development is not homogeneous but divided into high, medium, and low performance groups.

The cluster analysis empirically confirms that human development in West Nusa Tenggara remains spatially fragmented, dominated by the strong performance of the provincial capital and constrained progress in rural districts. The existence of three distinct clusters highlights that development disparities are not random but structurally embedded within the province's socio economic landscape. This pattern reinforces the need for policy attention to address regional inequality by focusing resources on lagging districts while maintaining the sustainability of growth in more advanced regions.

The findings of this study confirm that human development in West Nusa Tenggara (NTB) is far from homogeneous. The clear spatial clustering that emerged from the hierarchical analysis underscores the idea that human progress is neither automatic nor evenly distributed but instead is shaped by local socio economic contexts and by the unequal distribution of opportunities. This result is consistent with Amartya Sen's Capability Approach, which views development not as the accumulation of income but as the expansion of people's substantive freedoms and their capabilities to live the lives they value (Sen, 1999). The observed disparities in education, health, and income across NTB's districts illustrate different levels of these capabilities. Regions that fall within the low HDI cluster demonstrate limited opportunities to access quality education and productive livelihoods, which constrains their ability to transform resources into meaningful human outcomes.

The hierarchical clustering revealed three clearly differentiated groups, consisting of a high HDI cluster represented only by Mataram City, a medium HDI cluster made up of West Lombok and West Sumbawa, and a large low HDI cluster that includes the remaining seven regions. This pattern reflects a classic manifestation of spatial polarization and agglomeration economies, where development tends to concentrate in urban hubs that benefit from infrastructure, institutional capacity, and diversified economic activities. Over time, these centers attract both capital and skilled labor, creating what Myrdal once described as cumulative causation, which refers to a reinforcing cycle of growth in the core and stagnation in the periphery. The strong performance of Mataram City across all HDI dimensions, including education, health, and living standards, illustrates this mechanism clearly and shows that its advantage is not coincidental but rather structurally determined by its role as the province's economic, educational, and administrative center.

This study is consistent with the findings of Purnamasari, who demonstrated that regencies and cities in Central Java can be grouped into three HDI categories: high in urban areas, medium in transitional regions, and low in rural or peripheral areas (Purnamasari, et al., 2014). This pattern illustrates the existence of interregional development disparities similar to those found in this study. Rahmati also identified that most provinces in Indonesia fall into the medium HDI group, with only a few achieving the high category (Rahmati & Wijayanto, 2021). These findings confirm that inequality in education, health, and economic aspects remains a major factor distinguishing regional groups.

This study is also relevant to the findings of Mailien who found that regions with higher levels of education and income tend to form high-HDI clusters that are geographically concentrated, showing spatial interconnections among regions with similar levels of development (Mailien, et al., 2023). Talakua similarly observed a spatial polarization pattern in Maluku Province, where Ambon City is the only region with a high HDI, while surrounding regencies remain in the low category (Talakua, et al., 2017). This pattern is comparable to the situation in West Nusa Tenggara, where Mataram serves as a growth center with outstanding HDI performance. Furthermore, Fauzi highlighted the "core–periphery" polarization in East Java, where regions with high economic activity and better public infrastructure form high-HDI clusters, while peripheral regions with limited access to services are concentrated in the low-HDI group (Fauzi, et al., 2019). Ramadani also revealed that regions with higher welfare indicators tend to coincide with high-HDI groups, whereas those with lower welfare levels fall into the low-HDI group (Ramadani & Salma, 2022).

In addition, the findings of this study are consistent with previous research on spatial inequality in Indonesia. Fahmiyah and Ningrum used a K Means clustering approach to classify Indonesia's 34 provinces based on their HDI indicators and found that only a handful belonged to the high development cluster, while the majority were concentrated in medium or low clusters. Their study demonstrated that clustering methods are effective in capturing regional disparities in human development across a heterogeneous country such as Indonesia (Fahmiyah & Ningrum, 2023). Similarly, Agustine analyzed socio economic clustering in Lampung Province and found that spatial differentiation between urban and rural areas remained persistent, reinforcing the need for region specific policy design. Both studies strengthen the external validity of the present findings by showing that NTB's pattern of polarization mirrors a broader national tren (Agustine, 2025).

The results of this study are consistent with spatial economic theories that emphasize the role of agglomeration and urban concentration in shaping regional disparities. Glaeser explained that agglomeration economies arise when close spatial interactions among economic actors enhance productivity through mechanisms of sharing, matching, and learning. This concept helps explain why Mataram has emerged as NTB's core of human development, as the concentration of educational institutions, healthcare facilities, and economic activities generates multiplier effects that accelerate HDI improvement (Glaeser, 2010).

The findings also resonate with Spatial Mismatch Theory, initially proposed by Kain and later refined by Gobillon, Selod, and Zenou, which explains that inequalities often emerge when the residential locations of disadvantaged populations are spatially separated from centers of employment and social services. In NTB, the peripheral districts particularly those on Sumbawa Island face geographical and infrastructural barriers that limit human mobility and access to essential education and healthcare services (Gobillon, Selod, & Zenou, 2007).

Beyond Indonesia, comparable observations have been made in developing regions worldwide, where urban centers act as human development magnets. UNDP's Human Development Report 2023/24 notes that inequality within countries is increasingly driven by geographic concentration of opportunities, with metropolitan regions accumulating higher life expectancy, education, and income outcomes than rural areas (UNDP, 2023).

From a policy perspective, the results suggest that a one size fits all development strategy is unlikely to be effective because each cluster exhibits distinct structural characteristics that require different forms of intervention. Regions in the low HDI cluster, which make up the majority of NTB's districts, face overlapping challenges in education and income generation. These areas would benefit from targeted investments in basic education, vocational training, and healthcare access, which could gradually build human capital and improve productivity. The medium HDI cluster, which includes West Lombok and West Sumbawa, shows relatively better performance and could be supported through policies that encourage economic diversification, enhance the quality of secondary education, and stimulate local innovation. Meanwhile, Mataram City, as the high HDI outlier, should not only maintain its current achievements but also serve as a knowledge and capability hub that spreads best practices to neighboring regions.

Another noteworthy implication is the dominant role of education in determining differences in human development. The variation in expected and mean years of schooling contributed more significantly to the clustering results than either per capita expenditure or life expectancy. This finding is consistent with long standing evidence showing that education is the most elastic component of HDI because its improvement tends to accelerate overall human development more effectively than similar gains in income or health (UNDP, 2023). Education broadens people's capabilities, allowing them to access better employment, adopt healthier behaviors, and participate more actively in civic life. Therefore, focusing on education, especially at the lower secondary and upper secondary levels, could become the most strategic entry point for advancing NTB's human development agenda.

The discussion highlights that achieving inclusive human development in NTB requires policy design that is both regionally adaptive and based on empirical evidence. The cluster map produced in this study provides a practical framework for policymakers since it identifies the areas that should be prioritized for educational and welfare investments as well as those that can function as regional centers of growth. By implementing strategies that are specific to each cluster, the provincial government can improve resource allocation, promote faster regional convergence, and strengthen the equity aspect of NTB's overall development trajectory.

4. CONCLUSIONS

This study concludes that human development in West Nusa Tenggara (NTB) remains spatially unequal, with Mataram City dominating as the province's development hub while peripheral regions, particularly those on Sumbawa Island, continue to lag behind. Based on hierarchical cluster analysis of four Human Development Index (HDI) indicators, three distinct groups were identified, consisting of a high development cluster represented by Mataram City, a medium development cluster that includes West Lombok and West Sumbawa, and a low development cluster covering the remaining seven districts. This clustering, which was validated by the lowest Davies–Bouldin Index value of 0.4573, highlights that disparities arise from unequal access to education, healthcare, and economic resources. Therefore, adaptive and cluster specific policy strategies are essential, including efforts to improve basic and vocational education in low HDI regions, strengthen local economic diversification in medium clusters, and position Mataram City as a center for knowledge diffusion and development innovation.

Overall, the study emphasizes that reducing human development disparities in NTB cannot be achieved through uniform policy approaches. Inclusive and sustainable development must focus on expanding human capabilities as proposed by Amartya Sen's Capability Approach, with education serving as the main driver of improvements in human welfare. Future research is encouraged to use panel or time series data to analyze regional dynamics over time and to combine cluster analysis with causal methods in order to gain a deeper understanding of the factors that determine regional inequality.

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