A Comprehensive Analysis of Gender Disparities in Indonesian Human Development Using Machine Learning Techniques

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ABSTRAK: *Penelitian ini mengkaji kesenjangan gender dalam pembangunan manusia di berbagai wilayah Indonesia dengan menggunakan komponen Indeks Pembangunan Manusia (IPM). Kami menggunakan A/B testing, analisis komposit, dan K-means clustering. Dengan menganalisis data tahun 2023, kami mengungkapkan perbedaan gender yang signifikan dalam hal angka harapan hidup, pendidikan, dan kesejahteraan ekonomi. Meskipun perempuan menunjukkan angka harapan hidup yang sedikit lebih tinggi, laki-laki memiliki keunggulan dalam pendidikan danpengeluaran perkapita. Sebanyak 78,60% wilayah tergolong "Tinggi" untuk IPM laki-laki, dibandingkan IPM perempuansebesar 13,42%, dengan kesenjangan terbesar didaerah terpencil seperti Papua. Temuan kami menekankan perlunya kebijakan yang ditargetkan dan peka gender yang menanganikesenjangan regional dan mendorong akses yang adil. Penelitian ini memperdalam pemahaman tentang tantangan pembangunan gender di Indonesia dan memberikan wawasan untuk merumuskan strategi yang lebih efektif dalam mendorong pertumbuhan inklusif dan berkelanjutan.*

Kata kunci: *Ketidaksetaraan Gender, Indeks Pembangunan Manusia, Pembelajaran Mesin, Analisis Komposit*

ABSTRACT: *This study examines gender disparities in human development across various regions of Indonesia using components of Human Development Index (HDI). We employed A/B testing, composite analysis, and K-means clustering. By analyzing 2023 data, we revealed significant gender differences in life expectancy, education, and economic well-being. While women exhibit slightly higher life expectancy, men have an advantage in education and per capita expenditure. A total of 78,60% of regions is classified as "High" for male HDI, compared to just 13,42% for male HDI, with the largest gaps observed in remote areas such as Papua. Our findings highlight the need for targeted and gender-sensitive policies that address regional disparities and promote equitable access. This research deepens the understanding of gender development challenges in Indonesia and provides insight for formulating more effective strategies to foster inclusive and sustainable growth.*

Keywords: *Gender Inequality, Human Development Index, Machine Learning, Composite Analysis*

1. INTRODUCTION

Sustainable development is an approach that not only prioritizes economic growth as its main goal but also emphasizes improving the overall quality of life for people. This concept of development is defined as a process aimed at meeting the needs of the present without compromising the ability of future generations to meet their own needs. As Nasir et al., (2023) have articulated, this principle underscores the importance of a holistic and long-term approach in planning and implementing development. The essence of development is to enhance the quality of life and must positively impact human welfare comprehensively, addressing both physical and non-physical needs. One key indicator of development success is the Human Development Index.

The Human Development Index (HDI), introduced in 1990 by the United Nations Development Programme (UNDP), plays a crucial role in measuring the progress of a region or country in improving its citizens'quality of life. HDI is used to assess the impact of efforts to enhance basic human capital. A higher HDI indicates successful development, with more advanced and developed countries showing higher HDI scores. Factors influencing HDI include economic growth, regional revenue, and capital expenditure allocation (Najmi, 2019).

According to Fatmawati, (2024), there are three main dimensions of HDI for assessing the quality of life: health, education, and a decent standard of living. This aligns with Yektiningsih, (2018) who describes government performance through these three dimensions: Life Expectancy (AHH) as a health dimension, reflecting the average age a person can expect to live from birth, indicating access to healthcare and general health conditions. Expected Years of Schooling (HLS) and Mean Years of Schooling (RLS) represent the education dimension, showing the average years of education achieved by individuals in a specific age group, while expected years of schooling estimate the years of education that children starting school are expected to complete. Additionally, Per Capita Expenditure (PPK) reflects the standard of living, showing people's ability to spend on basic needs (Wiliyana, 2019).

Health, as a dimension in calculating the Human Development Index (HDI), directly reflects life expectancy (AHH) and individual, community, and national well-being (Basuki, 2020). Health indicators depict the quality of healthcare services and medical facilities in a region. Poor health not only reduces life expectancy but also impacts productivity and quality of life. Improving public health quality is a key achievement in health development. Thus, enhancing healthcare services, along with equitable and sustainable health programs, should be prioritized in development policies.

Education is another crucial dimension in the Human Development Index (HDI). Good education is measured by two indicators: Mean Years of Schooling (RLS), reflecting the level of education achieved, and Expected Years of Schooling (HLS), indicating access to education for school-age children (Rahminawati, 2023) . Quality and equitable education provides not only knowledge and skills but also enhances social, economic, and health awareness, contributing to increasing the HDI.

A decent standard of living, measured by Gross National Income per capita, is the third dimension in HDI measurement. Purchasing Power Parity (PPK) is used to assess income, reflecting development achievements in ensuring a decent life (Ginting & Lubis, 2023). Therefore, the perceived well-being of the population represents a decent standard of living, ultimately reflecting the impact of efforts to enhance basic human capital as measured by the HDI.

However, to gain a comprehensive understanding, HDI analysis must also consider gender disparities. Gender gaps in HDI can indicate inequalities in access to education, healthcare, and economic opportunities between males and females. A study by (UNDP, 2019) showed that countries with higher gender equality tend to have higher overall HDI scores. Therefore, attention to gender differences in HDI is crucial not only for social justice but also for improving the quality of life for all citizens. In modern development contexts, gender disparities are a significant concern as they reflect the extent to which development policies have balanced the well-being of both genders. Thus, in development analysis, it is essential to examine not only the overall HDI but also how HDI varies between males and females.

Summarizing these three dimensions into a single HDI variable is necessary. Composite Scoring and reliability assessment are important steps in data management and analysis. Composite Scoring, a widely used method in quantitative research, combines indicators representing variables to produce a single score or data point. George et al. (2016) discussed how composite scoring, as a statistical method, integrates health, education, and standard of living dimensions. This method simplifies data, facilitates comparisons, and allows further HDI analysis, such as identifying gender imbalances and disparities in human development.

To assess gender diversification at the HDI level, A/B testing and cluster-based models (Machine Learning) on the composite index results will be conducted. The clustering method employed using K-means Clustering (Hartigan & Wong, 1979). The K-means method is a data analysis technique for grouping data into clusters based on characteristics, in this case, gender-based HDI levels. The data are clustered based on similar characteristics in HDI dimensions, such as health, education, and standard of living, to facilitate identifying differences between males and females across regions in Indonesia.

Understanding gender disparities in key socio-economic indicators is critical for informing policies aimed at achieving gender equality and promoting human development. The Human Development Index (HDI), which includes components such as life expectancy (AHH), education (measured by HLS, and RLS), and income (represented PPK), serves as a vital metric in this regard. However, aggregate measures can often mask underlying disparities between different population groups, including those based on gender. One of the biggest challenges in the economy is gender disparities, which can affect a country's growth. Gender equality is directly related to issues such as poverty, educational inequality, healthcare access, and financial inclusion (Ramadhaniati, 2021). Therefore, efforts to understand and address gender disparities are key to driving comprehensive human development and ensuring that the benefits of economic growth are enjoyed by all segments of society.

This study will apply K-means clustering to analyze gender-based disparities in HDI across various regions in Indonesia. By identifying patterns within HDI components such as health, education, and income, we aim to uncover differences between male and female populations. The findings will contribute to a deeper understanding of how gender impacts human development and will inform policies aimed at reducing gender disparities in Indonesia.

2. METHOD

The analysis and modeling in this research were conducted using Python version 3.12.3, alongside various supporting libraries. Secondary data from the Central Bureau of Statistics (BPS) covering the period of 2023 were utilized. Data was obtained from the official BPS website, cleaned for better analysis and modeling, and combined with Geographic Information System (GIS) vector data for spatial analysis. ShapeFiles were sourced from www.igismap.com.

2.1 A/B testing

To rigorously assess differences between male and female HDI composite index, an adaptive AB testing approach was employed. This approach was guided by the need to ensure that the statistical tests used were appropriate for the data's characteristics, thereby enhancing the reliability and validity of the findings. The process began by ensuring that the classic assumptions of normality and homogeneity of variance were met:

1. **Normality Assumption**: The normality of the data distribution was assessed using the Kolmogorov-Smirnov (KS) test, which is particularly suitable for large sample sizes (greater than 500 observations). Data that passed this test ($p > 0.05$) were considered to meet the normality assumption.
2. **Homogeneity of Variance Assumption**: For datasets that were normally distributed, Levene's test was conducted to evaluate whether the variance across male and female groups was homogeneous.

Based on the outcomes of these preliminary tests, the following statistical methods were selected:

1. **Student's t-test** was conducted when both normality and homogeneity of variance were confirmed, ensuring that the data met the classic assumptions for parametric testing.
2. **Welch's t-test** was applied when the data were normally distributed but exhibited unequal variances, making it a more robust choice in the presence of variance heterogeneity.
3. **Mann-Whitney Utest** served as a non-parametric alternative when the normality assumption was violated, regardless of whether the variances were homogeneous or not.

To quantify the magnitude of the observed differences, **Cohen's d** was calculated as an effect size measure. Additionally, to control for the risk of Type I errors due to multiple comparisons, p-values were adjusted using the **Bonferroni method**. This comprehensive approach ensured that the most suitable statistical tests were applied, providing a robust evaluation of gender differences across the HDI component variables.

2.2 Composite Analysis

Composite analysis was employed to combine multiple variables into a single index or score, enabling a comprehensive evaluation of the Human Development Index components. This method aggregates different indicators that represent various dimensions of the phenomenon under research, allowing for a more holistic understanding. The Composite Analysis steps conducted in this research are:

1. **Variable Selection:** Individual variables for inclusion in the composite analysis which are the components of HDI were identified and determined based on their relevance.
2. **Standardization:** Each variable was standardized using z-scores to ensure they have the same mean and standard deviation, facilitating comparability.
3. **Aggregation:** An aggregation method was applied, where each variable was weighted according to its relative importance. In this study, four variables were used, with "expected year of schooling" and "mean year of schooling" assigned equal weights. The composite score was calculated by multiplying each standardized variable by its corresponding weight and summing the products.
4. **Analysis:** The resulting composite variable was then analyzed using statistical techniques such as correlation, regression, or factor analysis to explore its relationships with other variables or to identify patterns within the data.

2.3 K-means Clustering

K-means clustering is an unsupervised machine learning (ML) algorithm used to divide a dataset into k distinct clusters, grouping similar data points to uncover hidden patterns or structures. The algorithm iteratively assigns each data point to the nearest cluster centroid, recalculating the centroids after each assignment until it converges. K-means is widely applied in fields such as customer segmentation, image segmentation, and document clustering.

The foundational work on K-means clustering was conducted by Macqueen, (1967), detailed in his paper "*Some Methods for Classification and Analysis of Multivariate Observations.*" This work introduced the basic K-means algorithm, establishing the groundwork for its subsequent development and applications. For this research, the following steps were undertaken:

1. **Data Preparation:** Variables were standardized to ensure uniform contribution to distance calculations.
2. **Determination of Clusters (k):** The optimal number of clusters was determined using the elbow method, silhouette score, and Calinski-Harabasz index (CHI). These metrics assess cluster quality and cohesion, guiding the selection of the most appropriate k value.
3. **Clustering:** The K-means algorithm was executed, assigning each data point to the nearest cluster.
4. **Interpretation:** The resulting clusters were examined to identify distinct patterns or characteristics within each group, providing insights into the demographic segmentation of the Human Development Index by gender.

3. RESULT AND DISCUSSION

3.1 A/B Testing Result

The AB testing aimed to assess gender differences across four variables: *Angka Harapan Hidup* (AHH), referring to life expectancy; *Harapan Lama Sekolah* (HLS), representing expected years of schooling; *Rata-rata Lama Sekolah* (RLS), indicating mean years of schooling; and *Pengeluaran Per Kapita* (PPK), relating to per capita expenditure. The tests used included Student's t-test for AHH, Mann-Whitney U test for HLS and PPK, and Welch's t-test for RLS, revealing significant gender disparities for all variables.

Variable’s	Gender	Mean ± SD	Statistics Test	Adjusted p-value	Effect Size (Cohen's d)
AHH (Life Expectancy)	Male	68.30 ± 3.40	Student's t-test	0.0000	-1.15
	Female	72.21 ± 3.39			
HLS (Expected Years of Schooling)	Male	13.11 ± 1.26	Mann-Whitney U test	0.0001	-0.19
	Female	13.36 ± 1.39			
RLS (Mean Years of Schooling)	Male	9.05 ± 1.49	Welch's t-test	0.0000	0.43
	Female	8.36 ± 1.73			
PPK (Per Capita Expenditure)	Male	15255.05 ± 3663	Mann-Whitney U test	0.0000	1.84
	Female	8881.96 ± 3256			

Table 1. A/B Testing Results of Gender

For the AHH Value (life expectancy), males exhibited a lower mean (68.30 ± 3.40) compared to females (72.21 ± 3.39), with a large effect size (Cohen's d = -1.15), indicating substantial practical significance. Consistent with these findings Yusrya, (2023) also reported that female life expectancy (AHH) surpasses that of males.

The HLS Value (expected years of schooling) revealed a significant gender difference, with males (mean = 13.11 ± 1.26) showing lower averages than females (mean = 13.36 ± 1.39). The effect size was small (Cohen's d = -0.19), suggesting minor practical significance. Conversely, the RLS Value (mean years of schooling) indicated that males (mean = 9.05 ± 1.49) had higher values than females (mean = 8.36 ± 1.73), with a medium effect size (Cohen's d = 0.43), reflecting moderate practical significance. This is corroborated by the PUSDATIN-PUANRI (2022) report, which confirms that while males have higher mean years of schooling (RLS) compared to females, the expected years of schooling (HLS) for females is higher than that for males.

The most pronounced difference was observed in the PPK Value (per capita expenditure), where males (mean = 15,255.05 ± 3,663.88) had significantly higher values compared to females (mean = 8,881.96 ± 3,256.83), with a very large effect size (Cohen's d = 1.84), highlighting substantial practical significance. This is supported by Pusat Kebijakan Ekonomi Makro & Tim PUG 2021, (2022) who reported similar findings, demonstrating that per capita expenditure (PPK) for males is significantly and consistently higher than for females.

Overall, the results underscore significant gender differences across all four variables. While all variables show significant differences, the effect sizes vary: AHH Value and PPK Value exhibit large effect sizes, indicating substantial gender disparities; HLS shows a small effect size, reflecting a more subtle difference; and RLS presents a medium effect size, indicating a moderate difference. In line with the research conducted by Sakinah et al., (2023), it was found that Life Expectancy (AHH) and Per Capita Expenditure (PPK) have a positive and significant impact on the Human Development Index (HDI).

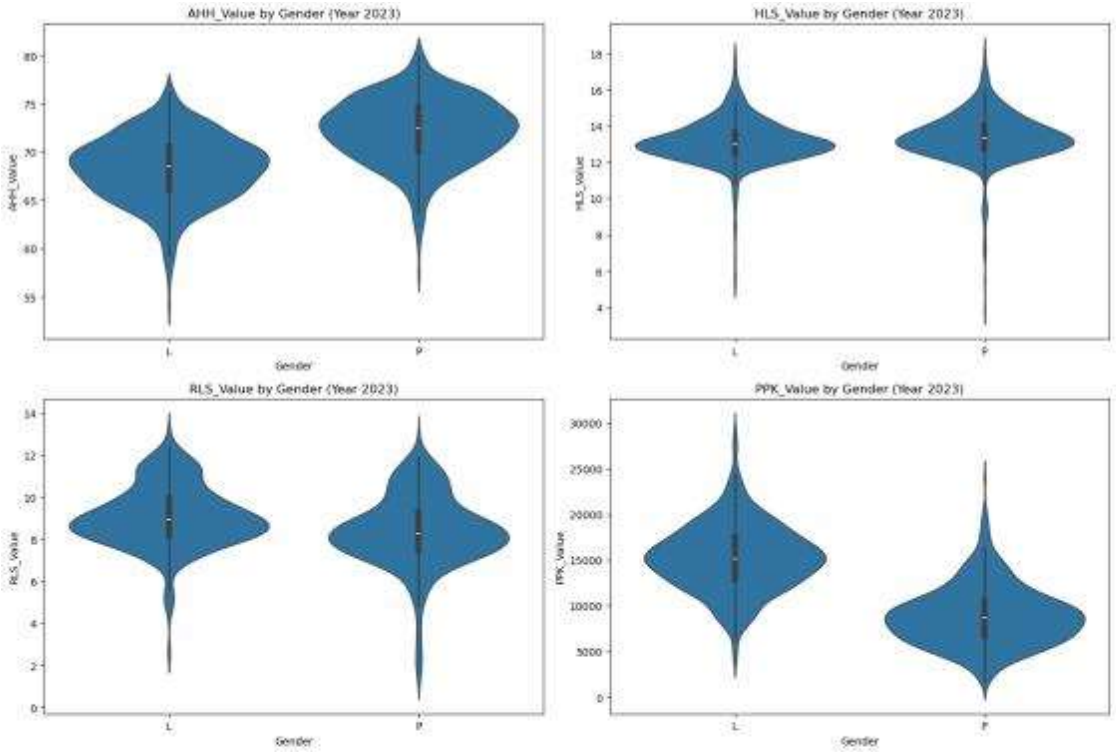

Figure 1. Violin Plot of HDI Components by Gender

The violin plots illustrated these differences by gender, enhancing the interpretability of the results. The comprehensive analysis underscores significant gender disparities across the variables, with varying degrees of practical significance, as indicated by the effect sizes.

3.2 Composite Analysis

The analysis presented focuses on the Human Development Index (HDI) differences across gender using a composite index approach. This composite index is constructed from four current critical indicators (3 dimensions). Each indicator is standardized, weighted according to its importance, and then combined to form a single composite index that encapsulates the overall human development level for both male (L) and female (P) populations.

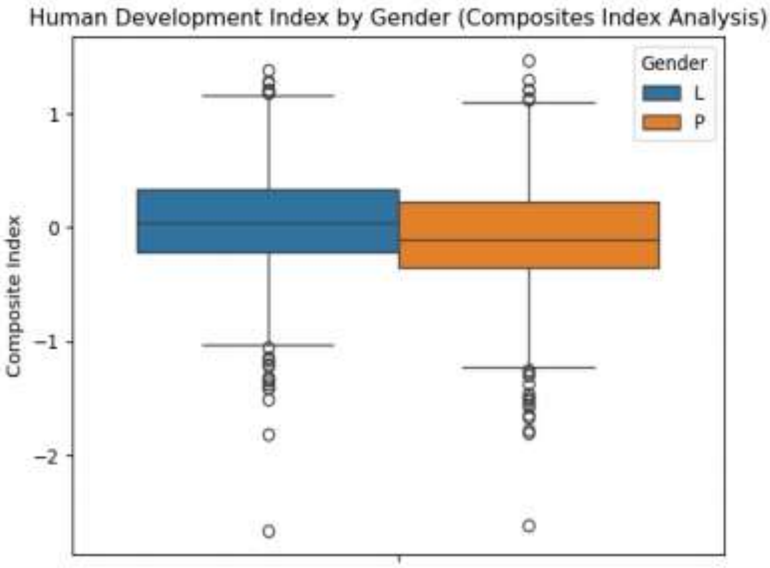

Figure 2. Composite Development Index by Gender

The graph x visualizes the distribution of this composite index for males and females. The central line within each box represents the median, with the interquartile range (IQR) captured by the box. The whiskers extend to 1.5 times the IQR, indicating the range within which most data points lie, while outliers are depicted as points beyond these whiskers.

The distribution of the composite index appears to be similar in terms of median values for both genders, suggesting that, on average, human development factors are comparable between males and females. However, the boxplot reveals some gender-specific differences. The male composite index distribution shows a slightly higher upper quartile, indicating a broader range of higher values among males. Additionally, the male distribution includes more outliers, suggesting greater variability in HDI across regions. In contrast, the female distribution is more compact, indicating less variability in human development outcomes.

These findings suggest that while overall human development levels may be similar across genders, the variability and range of these outcomes differ, with males showing a wider spread, particularly at higher levels of the composite index, and females demonstrating a more consistent development profile across regions. This nuanced gender difference highlights the importance of considering variability and distribution in HDI analysis, beyond just central tendency measures.

The results align with findings from the UNESCO Institute for Statistics, (2018), which highlight gender-specific disparities in educational and developmental outcomes. The broader range of outcomes observed among males, compared to the more consistent outcomes among females, can be interpreted through the concept of horizontal inequalities. These inequalities often manifest when culturally or regionally defined groups experience significantly different outcomes, not solely due to individual effort but due to underlying structural disparities.

Gender	Top 3 Regions	Composite Index	Low 3 Regions	Composite Index
L	1. Jakarta Selatan, DKI Jakarta	1.385	1. Peg. Bintang, Highland Papua	-1.509
	2. Yogyakarta, DI Yogyakarta	1.282	2. Puncak, Central Papua	-1.810
	3. Kota Salatiga, Central Java	1.271	3. Nduga, Highland Papua	-2.662
P	1. Yogyakarta, DI Yogyakarta	1.467	1. Asmat, South Papua	-1.780
	2. Jakarta Selatan, DKI Jakarta	1.294	2. Puncak, Central Papua	-1.801
	3. Banda Aceh, Nanggoroe Aceh Darussalam	1.207	3. Nduga, Highland Papua	-2.615

Table 2. Composite Index of Top and Low Three

The data reveals significant disparities in human development across different regions of Indonesia. Urban areas like **Jakarta Selatan** and **Yogyakarta** consistently rank among the top for both male (L) and female (P) populations, reflecting strong outcomes in education, health, and economic indicators. These regions demonstrate the benefits of well-developed infrastructure and access to resources.

In contrast, remote regions in **Papua**, such as **Nduga** and **Puncak**, consistently appear among the lowest-ranking areas for both genders. These regions face considerable developmental challenges, likely due to limited access to education, healthcare, and economic opportunities. The consistent low rankings for both male and female populations in these areas underscore the urgent need for targeted development efforts to address these disparities.

Overall, the data highlights a clear divide between urban centers, which exhibit high levels of human development, and remote areas, particularly in Papua, which lag significantly behind. In line with the research conducted by Sapkota, (2014), it was also found that good infrastructure and easy access to resources, such as electricity, clean drinking water sources, and road density, have a positive impact on the Human Development Index (HDI).

3.3 Clustering Composite Index

The analysis using K-means clustering with K = 2 divides the regions into two distinct clusters, representing 'High' and 'Low' composite indices. This choice is supported by the Elbow Method, Silhouette Score, and Calinski-Harabasz Index, all of which indicate that two clusters provide a clear and effective categorization of the data.

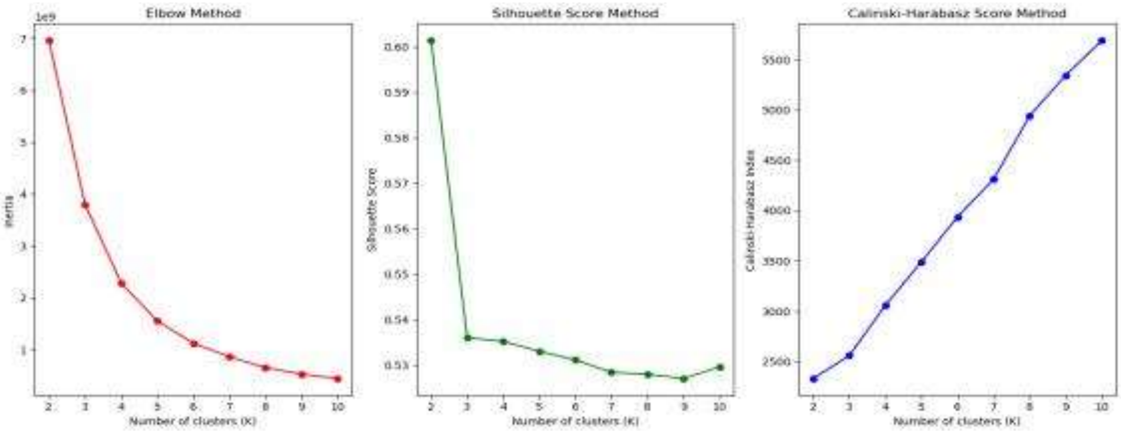

Figure 3. Visualization of Elbow, Silhouette Score, and Calinski-Harabasz Index Score

In the Elbow Method plot, a noticeable "elbow" starts at K = 2, suggesting that this number of clusters captures most of the data’s variance while maintaining simplicity. The Silhouette Score reaches its peak at K = 2, indicating that the regions within each cluster are more similar to each other than to regions in the other cluster. Finally, the Calinski-Harabasz Index shows a strong value at K = 2, reinforcing the idea that the data is well-separated into two clusters.

Cluster	Life Expectancy (AHH)	Expected Years of Schooling (HLS)	Mean Years of Schooling (RLS)	Per Capita Expenditure (PPK)
Cluster Low	70.51	13.03	8.08	8,448.19
Cluster High	69.95	13.48	9.44	16,316.43

Table 3. Result of Components Clustering in Years

With K = 2, regions are categorized into either a 'High' or 'Low' cluster based on their composite index, which integrates key human development indicators: life expectancy, expected years of schooling, mean years of schooling, and per capita expenditure.

1. High Index Cluster
   This cluster shows higher averages in both expected and mean years of schooling, as well as a substantially higher per capita expenditure. These figures suggest regions with better educational opportunities and stronger economic performance, which align with their classification as "High" in terms of overall human development.
2. Low Index Cluster
   This cluster has lower averages in educational attainment and per capita expenditure. This indicates regions with relatively stable health outcomes but significant challenges in education and economic development. overall living standards.

This comparative analysis of means between the two clusters underscores the multidimensional nature of human development and highlights the areas where each cluster excels or lags. The higher educational attainment and economic capacity align with the categorization as **Cluster High**, whereas **Cluster Low** reflects the challenges in education and economic output.

This analysis aligns with the research conducted by Santoso, (2019), which revealed that the characteristics of Cluster 1 (Low Index Cluster) are consistent with the findings of this analysis, characterized by low Years of Schooling (RLS) and low Per Capita

Expenditure (PPK). Similarly, Cluster 2 (High Index Cluster) shares the same characteristics as this analysis, with high RLS and high PPK.

3.4 Composite Cluster Distribution by Gender

Gender disparities in human development have long been a concern for policymakers and researchers alike. The Human Development Index (calculated by composite index), which integrates key indicators such as life expectancy, education, and per capita expenditure, provides a comprehensive measure of well-being across different regions. By analyzing the distribution of HDI clusters separately for males and females, we can gain insights into the extent and nature of gender inequalities. The following donut charts visualize the distribution of regions classified as either "High Index" or "Low Index" in the composite index analysis for both genders.

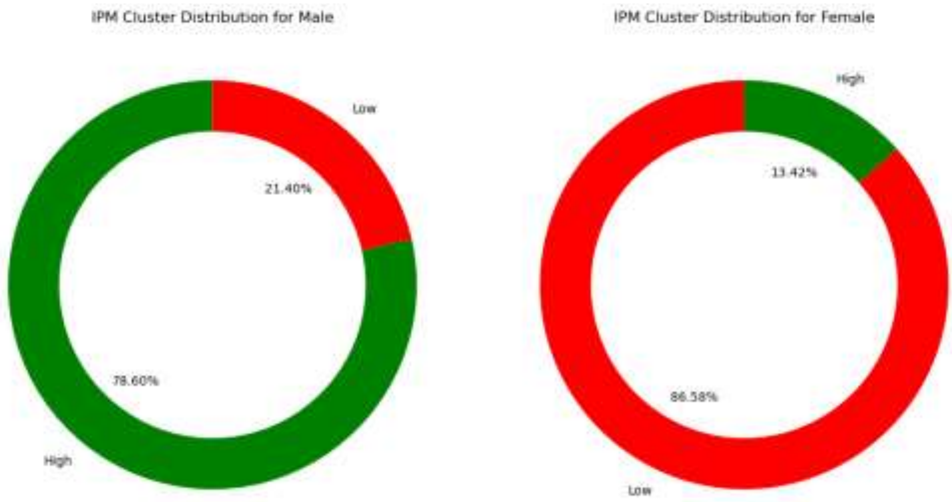

Figure 4. Percent Cluster Distribution of HDI Components by Gender

For the male population, the distribution shows that 78.60% of the regions are categorized as "High," while 21.40% are classified as "Low." This indicates that a substantial majority of the regions demonstrate strong composite index performance for males, suggesting relatively better outcomes in key human development indicators such as life expectancy, education, and economic status for men across these regions. In contrast, the distribution for the female population reveals a different pattern. Here, 86.58% of the regions fall into the "Low" category, with only 13.42% classified as "High." This stark difference suggests that the majority of regions are underperforming in terms of female human development indicators. The relatively smaller proportion of regions in the "High" cluster for females indicates disparities in educational attainment, economic opportunities, and health outcomes compared to males. The fact that certain regions show significantly better performance for men compared to women indicates the presence of gender-based discrimination. This discrimination is influenced by various factors, such as gender stereotypes embedded in society, differential treatment based on gender, and inequities in access to resources and opportunities. Factors that reinforce discrimination between men and women include patriarchal norms, low awareness of the importance of gender equality, and the imbalance of power between men and women (Pahlevi & Rahim, 2023).

The comparative analysis of these two charts underscores significant gender disparities in human development across the regions. While a majority of regions show positive development outcomes for males, the opposite is true for females, with most regions lagging in critical human development metrics. This imbalance highlights the need for targeted interventions and policies aimed at improving gender equality, particularly in regions where females are disproportionately represented in the "Low" development cluster. The findings suggest that without addressing these disparities, overall human development progress will remain uneven and inequitable across genders.

3.5 Cross-regions Composite Cluster Distribution by Gender

This research delves into gender disparities in development across Indonesia's provinces, focusing on regions where both male and female populations are classified as "High" in the Human Development Index (HDI). The analysis provides a detailed overview of gender parity in development outcomes, highlighting areas of success and regions that require further attention.

Figure 5. Regions Visualization of HDI Clustering by Gender Disparities

a. Provinces Leading in Gender-Equal Development

1. **Jakarta** stands out as the province with the highest achievement in gender-equal development, with 100% of its regions classified as "High Index" for both males and females. This indicates that the development policies in Jakarta are exceptionally effective in ensuring that both men and women equally benefit from economic, health, and educational advancements. This level of gender parity is rare and sets a benchmark for other provinces.
2. **Yogyakarta** (60%) and **Bali** (55.56%) also demonstrate significant success. These provinces have over half of their regions classified as "High" for both genders, suggesting that development benefits are more evenly distributed between men and women, reflecting a balanced approach to human development.

b. Provinces with Moderate Gender Parity

1. Provinces like **Central Java** (25.71%) and **East Java** (23.68%) show moderate success in gender-equal development. A quarter of their regions are classified as "High" for both males and females, indicating that while these provinces are on the right path, there is still considerable room for improvement. The disparity within these provinces suggests that while some areas have benefited from development, others may be lagging, particularly in achieving gender equity.

c. Provinces with Limited High Development for Both Genders

1. Provinces such as **West Java** (11.11%) and **North Sumatera** (6.06%) exhibit significant disparities in development outcomes, with a very low percentage of

regions where both males and females are classified as "High." This indicates challenges in extending the benefits of development to both genders equally. The uneven distribution of high-development regions reflects underlying socio-economic inequalities that affect men and women differently.

d. Provinces Lacking High Development for Both Genders

1. Several provinces, including **Gorontalo**, **Jambi**, **East Kalimantan**, and **West Sulawesi**, have 0% of regions where both males and females are classified as "High." This highlights a critical gap in development efforts, where neither gender sufficiently benefits from progress. These provinces may face structural challenges that hinder overall development, such as limited access to education, healthcare, and economic opportunities, impacting both men and women.

The findings provide a nuanced understanding of gender disparities in development across Indonesia. While certain provinces like Jakarta stand out as examples of successful gender-equal development, many other regions continue to struggle with significant inequalities. The uneven distribution of "High Index" development regions suggests that socio-economic, cultural, and policy-driven factors are crucial in determining gender outcomes. According to research conducted by Kusumawiranti, (2021), it was found that current development in Indonesia still largely implements exclusive policies rather than inclusive ones. However, social inclusion is crucial even at the smallest level of governance, such as within village administrations.

This research underscores the importance of targeted, gender-sensitive policies that address the unique challenges faced by men and women in different regions. It also highlights the need for a more inclusive approach to development that ensures equitable access to resources and opportunities for all. As Indonesia continues to grow and develop, these insights can inform policymakers and development practitioners in crafting strategies that promote gender equality and foster inclusive human development across the country.

3.6 CONCLUSION

This study reveals significant gender disparities in human development across Indonesia's regions through analysis of the Human Development Index (HDI) components. Our findings show that while females demonstrate higher life expectancy and expected years of schooling, males exhibit advantages in mean years of schooling and per capita expenditure. Urban areas consistently rank high in HDI for both genders, while remote regions, particularly in Papua, lag behind significantly. Strikingly, 78.60% of regions fall into the "High" HDI category for males, compared to only 13.42% for females, highlighting a critical gender gap in development outcomes.

These disparities underscore the need for targeted interventions and policy reforms. Efforts should focus on addressing gender-specific barriers in education, economic participation, and healthcare access, particularly in underserved regions. A nuanced, region-specific approach to development is crucial, considering local contexts and challenges. Policies should aim to promote gender equality in educational attainment and economic opportunities, while also working to bridge the urban-rural development gap.

In conclusion, addressing gender disparities is essential for achieving inclusive and sustainable development across Indonesia. Future research should explore longitudinal trends and investigate the intersectionality of gender with other socio-economic factors. By leveraging these insights, policymakers and development practitioners can work towards a more equitable future where both men and women have equal opportunities to thrive and contribute to Indonesia's growth and prosperity.

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