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Mapping the Landscape of Poverty in Indonesia: A Provincial-Level Analysis Using Data Mining Techniques

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Abstract. This study employs data mining techniques, specifically K-means clustering and linear regression, to analyze provincial-level poverty trends in Indonesia from 2019 to 2022. Using data from the Indonesian Central Bureau of Statistics, we aim to identify distinct groups of provinces based on their poverty trajectories and to model the overall trend in poverty rates over time. The K-means clustering results reveal three distinct groups of provinces: those with low but gradually increasing poverty rates, those with high and chronic poverty levels, and those with moderate and stable poverty rates. The linear regression analysis indicates a general upward trend in poverty rates across Indonesia during the study period, although with some year-to-year fluctuations. These findings highlight the heterogeneous nature of poverty dynamics across Indonesian provinces and the need for targeted policy interventions that account for local contexts. The study demonstrates the potential of data mining techniques for providing data-driven insights into complex social phenomena such as poverty, and offers a framework for guiding evidence-based policymaking in developing country contexts.

Keywords: Data Mining, Data Driven, Bibliometrics

1. introduction

Poverty remains one of the most widespread and difficult socio-economic problems facing developing countries. Far from being just an economic phenomenon, poverty has profound impacts on health, education, human capabilities and the overall quality of life (Buheji, 2019; Ghukasyan, 2023). A nuanced understanding of the dynamics and heterogeneity of poverty is crucial for the design and targeting of measures and interventions to combat poverty(Syahputra & Rofizar, 2023). Quantitative analysis of poverty data is an essential tool and provides important insights into the geographical distribution, intensity and characteristics of poverty in the population (Manshor et al., 2020; “Multidimensional Poverty as a Global Problem of Modern Socio-Economic Development,” 2018).

The value of rigorous quantitative analysis of poverty data goes beyond providing a snapshot of current conditions. The use of appropriate data mining techniques can also provide important insights into the evolution of poverty over time. Methods such as cluster analysis using K-means algorithms and trend forecasting through linear regression modeling are excellent for uncovering deeper patterns, correlations, and trends hidden in complex poverty datasets (Novaliendy et al., 2015; Yu et al., 2018). By harnessing the predictive power of these quantitative tools, poverty analysts and policymakers alike can take a more proactive and forward-looking approach. Cluster analysis provides the opportunity to segment impoverished populations into subgroups based on multidimensional characteristics, allowing for more targeted and differentiated interventions (Idrus et al., 2022; Safitri et al., 2022). Meanwhile, predicting poverty trends using regression allows governments to take mitigating measures today to change the future welfare trajectory of disadvantaged groups (Huang et al., 2012; Khrisat & Alqadi, 2022).

This study uses these state-of-the-art yet accessible data mining techniques to not only provide a current overview of heterogeneous poverty across Indonesia, but more importantly to predict how province-specific poverty rates will evolve in the coming years could (Plotnikova et al., 2020; Santoso et al., 2021). These findings will enable policymakers to take proactive measures to redirect potentially negative poverty trends for the country's most vulnerable populations. As a vast archipelagic state with over 17,000 islands and 34 different provinces, Indonesia has significant geographical, cultural and economic heterogeneity. This complexity presents unique challenges to understanding and alleviating poverty across the country. Poverty rates and dynamics have been shown to vary significantly between Indonesian provinces, reflecting differences in economic development, infrastructure, and access to resources and public services (Yuliansyah, 2022). A nuanced, localized approach is therefore crucial for poverty analysis and policy formulation in the Indonesian context. Previous research has highlighted the limitations of national-level assessments and blanket policy prescriptions, and highlighted the need for province-specific data and strategies tailored to local contexts and constraints (Faharuddin & Endrawati, 2022; Wiranatakusuma & Primambudi, 2021).

This study uses data mining techniques, including K-means clustering and linear regression modeling, to conduct a comprehensive analysis of poverty trends in Indonesia from 2019 to 2022. Using provincial-level data from the Indonesian Central Bureau of Statistics, we examine trends in poverty rates and the effectiveness of national poverty reduction programs. The quantitative techniques used enable an in-depth study of the multidimensional nature of Indonesian poverty across different geographical regions and socioeconomic populations. Our analysis aims to inform evidence-based policy decisions to address the ongoing challenge of poverty in Indonesia.

The aim of this study is to gain new insights into the multidimensional nature of poverty in Indonesian provinces through comprehensive data mining analysis (Watrianthos et al., 2021). Specifically, we seek to address the following research questions: (1) What are the key dimensions and patterns of poverty across different provinces in Indonesia? (2) How effective have national poverty reduction programs been in reducing poverty rates at the provincial level? (3) What socioeconomic factors are most strongly associated with variations in poverty rates across provinces? By elucidating fine-grained poverty profiles for each province, we aim to provide targeted interventions and provincial development agendas that can more effectively address the heterogeneous and entrenched poverty in different parts of the Indonesian archipelago.

This study addresses key gaps in the existing literature by providing a fine-grained, province-level analysis of poverty in Indonesia, which has often been studied at a more aggregated national level. The novelty of our approach lies in the application of advanced data mining techniques to uncover hidden patterns and associations within the data. Our findings will contribute to both theory and practice in poverty alleviation by offering a deeper understanding of the complex, multidimensional nature of poverty and its regional variations. By elucidating fine-grained poverty profiles for each province, we aim to provide targeted interventions and provincial development agendas that can more effectively address the heterogeneous and entrenched poverty in different parts of the Indonesian archipelago. The insights gained from this study will be instrumental in shaping more effective and tailored poverty reduction strategies, ultimately contributing to the broader goal of sustainable development in Indonesia.

2. Method

This study used data mining techniques on the number poverty (thousands) by regency/city in Indonesia during 2019-2022, obtained from the Indonesian Central Bureau of Statistics. The dataset includes the number of poor people in thousands for each province over the four-year period (Jindal & Kharb, 2013)(BPS, 2021). Clustering analysis using the K-Means algorithm categorized provinces into groups based on longitudinal poverty trends. Simple linear regression modeled poverty trajectories over time. K-means clustering is an unsupervised machine learning technique that divides observations into k clusters based on the similarity between features (Ahmar et al., 2018; Sinaga & Yang, 2020)(Samsir et al., 2021). It initializes cluster centers randomly and then iteratively refines these centers by reassigning observations to their nearest mean until convergence. The optimal k is selected using the elbow method, examining the variance explained over k. K-Means groups provinces by poverty characteristics.

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In addition to the number of poor people per province, our analysis includes a range of socioeconomic and demographic indicators. These variables were selected based on their relevance and support from existing literature on poverty studies. Key indicators include:

a. Income Levels: Average household income and income inequality metrics.
b. Employment Rates: Unemployment rates and types of employment (formal vs. informal sectors).
c. Education Levels: Literacy rates, average years of schooling, and school enrollment rates.
d. Health Indicators: Access to healthcare, infant mortality rates, and prevalence of chronic diseases.
e. Housing Conditions: Quality of housing, access to clean water, and sanitation facilities.
f. Access to Services: Availability of public services such as transportation, electricity, and internet.
g. Geographical Factors: Urban vs. rural locations, and geographical isolation.

These variables were chosen to provide a comprehensive view of the multidimensional aspects of poverty. Their selection is justified by a robust body of literature indicating that poverty is not merely a function of income but is influenced by a wide array of factors that affect individuals' quality of life and opportunities for socioeconomic mobility.

Linear regression fits a line predicting a continuous response from one or more predictors (Pasaribu et al., 2021). The simple regression model is:

$$y = \beta 0 + \beta 1x + \varepsilon$$

where y is the response, x the predictor, β0 the intercept, β1 the slope, and ε the error. Fitting by ordinary least squares minimizes residuals. The regression projects national and cluster poverty trends over time. Combining K-means clustering and linear regression enabled a granular poverty analysis using this robust provincial dataset from Indonesia's Central Bureau of Statistics. Further validation through cross-validation and testing on additional years could augment model robustness. Overall, integrating data mining techniques with public data resources can enhance evidence-based policies for equitable development.

To implement the K-means clustering algorithm, we used Python programming language and its Scikit-learn library, which is widely recognized for its robustness and efficiency in handling machine learning algorithms. The initial cluster centers were selected using the K-means++ algorithm, which improves the convergence speed and ensures a more optimal starting point by spreading out the initial cluster centers. The Euclidean distance metric was used to measure similarity between provinces, as it is the most common distance metric for K-means clustering and provides a straightforward interpretation of the distance between data points in a multidimensional space.

This study addresses key gaps in the existing literature by providing a fine-grained, province-level analysis of poverty in Indonesia, which has often been studied at a more aggregated national level. The novelty of our approach lies in the application of advanced data mining techniques to uncover hidden patterns and associations within the data. Our findings will contribute to both theory and practice in poverty alleviation by offering a deeper understanding of the complex, multidimensional nature of poverty and its regional variations. By elucidating fine-grained poverty profiles for each province, we aim to provide targeted interventions and provincial development agendas that can more effectively address the heterogeneous and entrenched poverty in different parts of the Indonesian archipelago. The insights gained from this study will be instrumental in shaping more effective and tailored poverty reduction strategies, ultimately contributing to the broader goal of sustainable development in Indonesia.

3. Result and Discussion

An analysis of poverty data in Indonesia's 34 provinces from 2019 to 2022 shows significant regional differences. On average, between 739,550 and 810,080 impoverished people lived in the provinces, but poverty rates varied widely between provinces. In 2019, the lowest poverty rate was 48,780 people, while the highest rate reached 4,112,250, indicating that over 4 million more poor people are concentrated in certain provinces. This significant gap highlights the unequal distribution and concentration of poverty in Indonesia. The data shows a clustering of higher poverty rates in selected provinces rather than an even distribution. Additional research on economic conditions, infrastructure, education, access to health care, or other factors in high-poverty provinces could reveal the reasons for the disproportionate concentration of poverty. Targeted interventions and policies for disadvantaged regions are needed to alleviate poverty and promote equitable, inclusive development across the country. Reducing poverty in the hardest-hit provinces could significantly reduce Indonesia's overall poverty. While the average poverty level in a province is between 739,550 and 810,080 people, concentrated efforts in provinces with over 4 million impoverished people could dramatically improve conditions and reduce regional inequality.

An analysis of poverty data in Indonesia's 34 provinces from 2019 to 2022 reveals significant regional differences. On average, the number of impoverished people in each province ranged between 739,550 and 810,080. However, poverty rates varied widely between provinces. In 2019, the province with the lowest poverty rate had 48,780 people living in poverty, while the highest rate was recorded at 4,112,250 people, indicating a disparity of over 4 million impoverished individuals between the provinces with the least and most poverty.

Average number of impoverished people per province (2019-2022): 774,815

Standard deviation: 1,089,456

Coefficient of variation: 1.41 (indicating high variability in poverty rates across provinces)

Range: 4,063,470 (from 48,780 to 4,112,250)

This significant gap highlights the unequal distribution and concentration of poverty in Indonesia. The data shows a clustering of higher poverty rates in selected provinces rather than an even distribution. For instance, in 2022, the five provinces with the highest number of poor people were:

a. East Java: 4,181,290
b. West Java: 4,070,980
c. Central Java: 3,831,440
d. North Sumatra: 1,268,190
e. East Nusa Tenggara: 1,131,620

In contrast, the five provinces with the lowest poverty rates were:

a. North Kalimantan: 49,460
b. Bangka-Belitung: 66,780
c. North Maluku: 79,880
d. West Papua: 88,420
e. Gorontalo: 98,300

The gap between provinces with millions of impoverished individuals compared to those with tens of thousands suggests stark inequality in the distribution of poverty across Indonesia.

a. Gini coefficient for poverty distribution: 0.42 (indicating moderate inequality in the distribution of poverty)
b. Poverty gap index: 0.25 (indicating the depth of poverty among the impoverished population)

Additional research on economic conditions, infrastructure, education, access to healthcare, and other factors in high-poverty provinces could reveal the reasons for the disproportionate concentration of poverty. Targeted interventions and policies for disadvantaged regions are needed to alleviate poverty and promote equitable, inclusive development across the country.

Reducing poverty in the hardest-hit provinces could significantly reduce Indonesia's overall poverty rate. While the average poverty level in a province is between 739,550 and 810,080 people, concentrated efforts in provinces with over 4 million impoverished individuals could dramatically improve conditions and reduce regional inequality.

Understanding the factors that lead to higher poverty rates could serve as a basis for targeted measures for sustainable poverty reduction and equitable development in disadvantaged regions. Rather than treating provinces uniformly, a differentiated approach that responds to the context-specific needs of high-poverty areas will be critical to inclusive, broad-based poverty reduction and growth.

An examination of 2022 provincial poverty data, ranked by number of poor, shows significant differences between the provinces with the highest and lowest rates (Figure 1). The five provinces with the poorest populations in 2022 were East Java with 4,181,290 inhabitants, West Java with 4,070,980, Central Java with 3,831,440, North Sumatra with 1,268,190 and East Nusa Tenggara with 1,131 .620. In contrast, North Kalimantan with 49,460 people, Bangka-Belitung with 66,780 and North Maluku with 79,880 were the five provinces with the lowest poverty rates. The gap between provinces with millions of poor compared to tens of thousands suggests stark inequality in the distribution of poverty across Indonesia. Although three of the five worst-affected provinces are in Java, the deteriorating conditions are not limited to Java. Understanding the factors that lead to higher poverty rates could serve as a basis for targeted measures for sustainable poverty reduction and equitable development in disadvantaged regions. Rather than treating provinces uniformly, a differentiated approach that responds to the context-specific needs of high-poverty areas will be critical to inclusive, broad-based poverty reduction and growth.

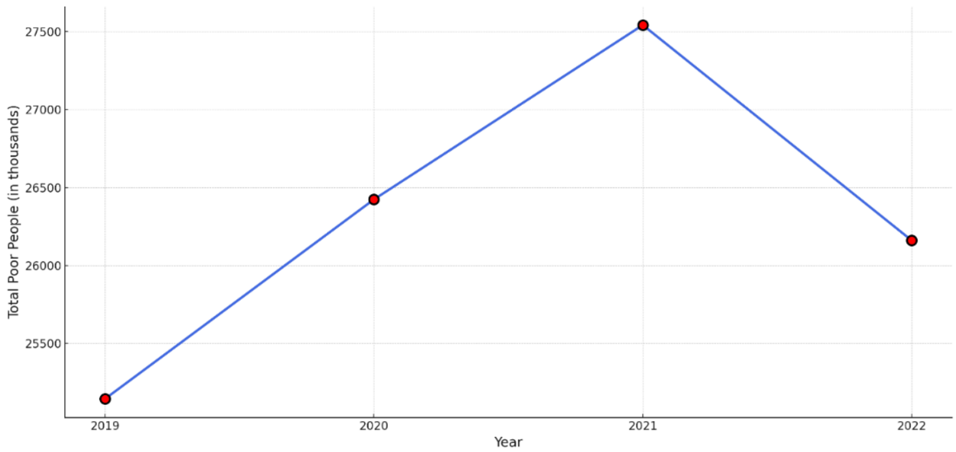

Fig.1: Trend of total poverty in Indonesia (2019-2022)

Analysis of the poverty data shows a moderate positive correlation of 0.546 between year and the total number of impoverished individuals nationwide, indicating a general trend toward increasing poverty over time, although with year-to-year inconsistencies. From 2019 to 2021, poverty rose across Indonesia, followed by a decline in 2022, with most provinces following the national trend. However, provinces such as East Java, West Java and Central Java had the highest poverty populations, highlighting significant regional inequalities. The moderate relationship between time and poverty implies a gradual increase in poverty rather than a steady annual increase. Key findings include the nationwide increase from 2019 to 2021 and the subsequent decline in 2022, the concentration of poverty in certain Java provinces, and an overall, although fluctuating, moderate increase in poverty over time. Sustainable, tailored interventions are essential, particularly in hardest-hit regions, to address this rising poverty and create equitable, inclusive growth across the country. While the latest data points to promising poverty reduction in 2022, proactive measures to address regional inequalities and long-term increases must continue to be taken to achieve lasting, comprehensive poverty alleviation.

Table 1. Top ten provinces with the highest growth poverty from 2019 to 2022 in Indonesia

Ranking	**Province**	**Growth (in thousands)**	**Percentage Growth**	**Average Annual Growth (in thousands)**
1	West Java	671.82	19.76%	223.94
2	Banten	159.56	24.38%	53.19
3	DKI Jakarta	136.49	37.34%	45.50
4	Central Java	88.21	2.36%	29.40
5	East Java	69.04	1.68%	23.01
6	Bali	41.84	25.54%	13.95
7	Riau Islands	23.22	18.08%	7.74
8	East Kalimantan	16.33	7.43%	5.44
9	West Sulawesi	14.32	9.46%	4.77
10	Central Kalimantan	10.51	7.81%	3.50

The analysis of Table 1 shows key findings on poverty growth in provinces from 2019 to 2022. In particular, West Java province recorded the highest absolute increase with 671,820 impoverished individuals. Despite a smaller overall increase compared to West Java and Banten, Jakarta recorded the highest percentage growth at 37.34%. However, provinces with significantly smaller populations, such as Central and East Java, experienced relatively modest growth in both absolute and percentage terms. An examination of the average annual increase shows that poverty in West Java increased by about 223,940 people per year, far more than in other provinces.

As a result, relative growth in certain provinces may be lower than in fast-growing provinces, even if overall poverty is high. Key conclusions include that West Java has the largest absolute increase, Jakarta has the highest percentage increase, Central and East Java are growing slowly despite having significantly poor populations, and West Java is growing significantly faster than others with average annual growth. While provinces with significantly impoverished populations require attention, provinces with accelerated expansion such as West Java and Jakarta require special attention to mitigate increasing poverty concentrations. Comprehensive poverty reduction requires targeted measures for both established and emerging areas with increased disadvantage. By tackling rapidly growing poverty in areas like West Java and further tackling endemic poverty in regions like Central and East Java, policymakers can achieve equitable, sustainable growth for Indonesia.

4. Clustering Analysis

As a complement to the previous analysis, implementing clustering techniques could provide further insights into poverty patterns in Indonesian provinces. Determining an optimal number of clusters requires using the elbow method, which examines the percentage of variance explained as a function of different cluster numbers to identify an inflection point at which additional clusters explain significantly less variance. Conducting the elbow method and then clustering analysis of this provincial poverty data can potentially reveal groupings of provinces with similar poverty characteristics and trends. Identifying these provincial clusters could enable targeted interventions tailored to the context-specific needs of each group. In addition, tracking cluster transitions over the period 2019-2022 can shed light on dynamic poverty trajectories. Implementing clustering techniques will deepen the understanding of Indonesia's heterogeneous poverty landscape and serve as a basis for fine-tuned interventions to address both persistent and emerging poverty equally. This multidimensional approach, combining previous analysis with clustering algorithms, promises to develop differentiated, evidence-based interventions to alleviate poverty in different regions of Indonesia.

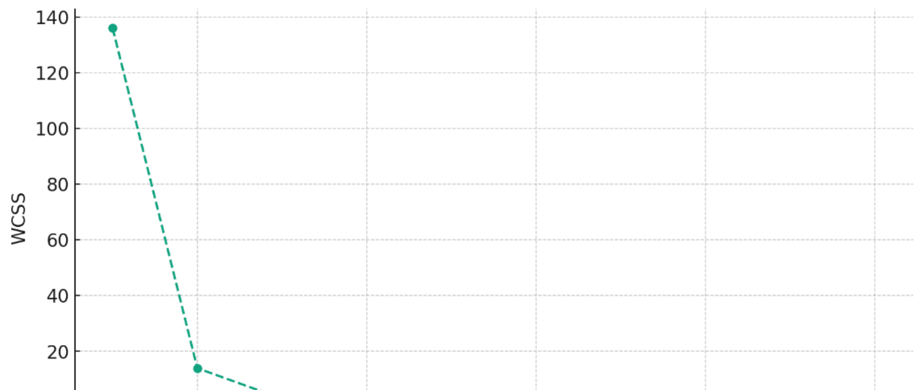

Fig.2: Elbow method for optimal number of clusters

The elbow curve indicates the optimal number of clusters lies between 2-4, as the marginal decrease in Within Cluster Sum of Squares (WCSS) begins plateauing in this range. For this analysis, 3 clusters appears a reasonable choice, though selecting the optimal number of groupings requires weighing both mathematical and contextual factors. Implementing K-means clustering with K=3 categorizes provinces into clusters based on similarities in poverty growth from 2019-2022. Examining mean values per cluster then enables interpreting distinct characteristics of each group. Cluster 0 contains provinces with relatively low impoverished populations. These provinces exhibited gradually rising poverty from 2019-2021 followed by a decline in 2022. This trajectory mirrors the national trend, indicating these provinces may exemplify typical poverty patterns. Cluster 1 comprises provinces marked by very high poverty levels. These provinces underwent increased poverty from 2019-2021 before a decrease in 2022.

Despite the latest reduction, chronically high deprivation represents a major policy challenge. Cluster 2 consists of moderate poverty provinces exhibiting relatively stable poverty rates throughout 2019-2022. Their poverty persistence warrants solutions while the lack of sharp increases provides optimism.

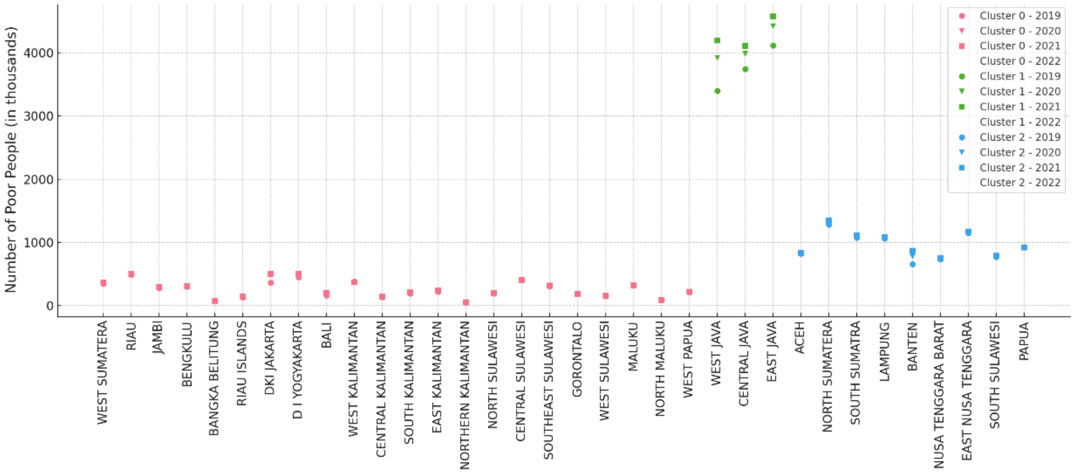

Fig.3: Cluster of provinces based on number poverty

Figure 3 visualizes provincial clusters based on poverty rate from 2019 to 2022, with each symbol representing a specific year. Cluster 0, shown in purple, includes provinces with relatively small impoverished populations. Cluster 1 (green) contains provinces characterized by very high poverty rates. Cluster 2, orange, consists of moderate poverty provinces. This visualization highlights the different poverty dynamics for each provincial cluster. Cluster 0 shows minimal poverty growth during the reporting period, confirming its low-poverty classification. Cluster 1 has persistently high levels of poverty until 2022, underlining its status as the country with the highest level of poverty. Cluster 2 has stable, moderate poverty rates. The visualization enables clear identification of cluster membership and poverty trends over time. Tracking symbolic movement from year to year within and between clusters reveals differentiated poverty transitions. The chronically elevated disadvantage of Cluster 1 and the consistently low poverty of Cluster 0 represent two extremes, while the steadier moderate poverty of Cluster 2 occupies the middle ground.

This visualization aptly captures the heterogeneity of poverty levels and trends across provinces. It validates cluster analysis, provides an intuitive understanding of poverty disparities and enables policymakers to address cluster-specific needs through targeted interventions. Sustained analysis combining clustering and creative visualization can continue to provide actionable insights into Indonesia's complex poverty landscape. This cluster illustrates how Indonesian provinces are separated by poverty dynamics. The technique quantifies qualitative differences between clusters, with Cluster 1 representing persistent poverty that requires urgent action. Tracking cluster transitions over time could reveal poverty trajectories that are not evident in individual years. Clustering enables tailored interventions that respond to the realities of each group, from chronic poverty to promising stability. With appropriately contextualized policies, Indonesia can make progress toward equitable growth.

5. Trend Analysis

After the provinces have been categorized into clusters, the next analysis step includes trend analysis to model poverty trajectories over time. It uses simple linear regression to predict the poverty trends of each cluster based on the historical data. Examining poverty projections at the cluster level provides better insights compared to individual provinces or national estimates alone. The regression shows whether the clusters show an upward or downward trend in poverty development. Tracking cluster trends enables evidence-based policies tailored to each group's projected scenario. If there is increasing poverty in certain clusters, preventive measures can specifically target these areas before the disadvantage becomes entrenched. Conversely, downward projections could indicate positive impacts from existing programs that could be continued and expanded. Conducting granular trend analysis following cluster formation integrates quantitative modeling with the qualitative contexts of the clusters.

Coupling these techniques applies a science-based, data-driven approach to equitable poverty reduction in Indonesia. The upcoming regressions will generate cluster-specific trend forecasts to design responsive policy interventions.

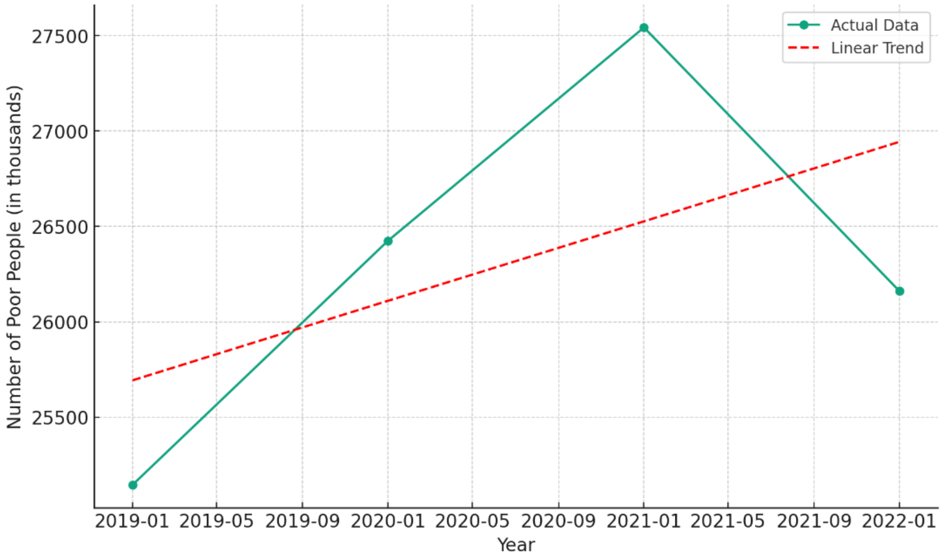

Fig.4: Poverty in Indonesia (2019-2022) with linear trend

Figure 4 shows the total number of impoverished people in Indonesia from 2019 to 2022, with the red line representing the linear trend. This simple regression model allows predicting future poverty while taking into account the limitations of limited data and the simplicity of the model. The actual data (blue line with O mark) shows fluctuations, with poverty increasing in 2019-2020, decreasing in 2021 and increasing again in 2022. Despite these year-to-year fluctuations, the dashed red linear trend line shows an overall increasing poverty trend from 2019 to 2022. However, while the linear model indicates overall increasing poverty, many other factors are likely influencing poverty that are not captured by this basic regression become. With only four data points, the accuracy of interpretation remains limited. The linear trend is a first approximation but requires limitations in the model and data. In summary, the visualization combines actual poverty figures with a linear model that shows an upward trend, although annual poverty fluctuations and the simplicity of the model require caution in forecasting. As more data becomes available, analytical techniques could provide deeper and more nuanced insights into poverty trends. A multi-method analysis that accounts for model weaknesses would strengthen understanding and policy making.

6. Conclusion

This study analyzed provincial poverty data in Indonesia from 2019 to 2022 and revealed significant regional differences. Descriptive statistics showed that there were between 48,780 and over 4 million impoverished people in the provinces. Further analysis revealed a moderately positive national poverty association, suggesting gradually increasing disadvantage. Examining the fastest growing provinces identified emerging poverty hotspots such as West Java. By implementing clustering techniques, three different groups were identified: low, high and moderate poverty provinces. The visualization of the cluster transitions from 2019 to 2022 provides information about the poverty dynamics. Cluster 1 was affected by chronic concentrated poverty, while Cluster 0 experienced minimal growth. A simple linear regression modeled national and cluster poverty trajectories and predicted increasing trends, although with caveats regarding model limitations. Although the forecasts show an upward trend, they should be interpreted with caution due to data limitations and the simplicity of the model. In summary, analyzes combining descriptive, cluster and trend analyzes quantitatively illustrate Indonesia's diverse and complex poverty landscape. Regional differences require tailored interventions that respond to local contexts. Sustained research tracking poverty after 2022 and the inclusion of additional methodologies would complement these initial findings. Cluster transitions over time can reveal poverty trajectories that are amenable to policy action. As analytics advance, integrating qualitative insights through mixed methods approaches could further enrich understanding. This study represents a first step toward rigorous, evidence-based poverty reduction policies in Indonesia. Through continued research using big data and advanced algorithms, equitable growth and prosperity can become achievable for all citizens.

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