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Determinants of Poverty Vulnerability in Underdeveloped Regions of Indonesia: Micro and Macro Economic Approaches

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Abstract: Poverty is a complex and multidimensional issue, particularly in Indonesia's underdeveloped regions. This study focuses on poverty vulnerability, defined as the risk of a household falling into poverty due to social, economic, or environmental shocks. Utilizing data from 26 underdeveloped districts, this research identifies determinant factors such as access to clean water, lighting, education, infrastructure, and geographical conditions. Discriminant analysis is applied to evaluate the contribution of these variables in predicting poverty vulnerability. The results indicate that nearly half of the underdeveloped regions are in a state of high vulnerability, caused by development inequality, lack of infrastructure, and low quality of human resources. This study emphasizes the importance of more inclusive policies to improve access to basic services and infrastructure in underdeveloped regions to reduce vulnerability to poverty and achieve sustainable development targets. These findings provide critical insights for designing more targeted policy interventions in alleviating poverty in Indonesia's underdeveloped areas.

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INTRODUCTION

Poverty remains a persistent structural challenge for Indonesia, despite positive trends in microeconomic and macroeconomic indicators. According to data from the Central Statistics Agency (BPS), the percentage of people living in poverty has declined, but this decline has not been evenly distributed across the country. There is still a striking gap between urban areas and regions categorised as 'underdeveloped'.

Poverty is a complex and multidimensional global issue, including in Indonesia, which possesses numerous underdeveloped regions. This issue is a top priority in the 2019–2024 National Medium-Term Development Plan (RPJMN) and the Sustainable Development Goals (SDGs). Underdeveloped regions in Indonesia, which are determined based on criteria such as community economy, human resources, and infrastructure accessibility, are characterised by higher vulnerability compared to other regions. Several of these underdeveloped regions have become the focus of accelerated development due to limited access to basic services and fiscal inequality (Mailyn & Kartika, 2025; Kemenko PMK, 2024).

Underdeveloped regions, scattered across various provinces in Indonesia, exhibit high poverty rates and remain far from national targets. Unfortunately, poverty research often focuses on urban areas, resulting in relatively less attention to poverty in underdeveloped regions.

Poverty in underdeveloped areas encompasses not only material limitations but also vulnerability—the risk of households falling into poverty due to social, economic, or environmental shocks. The World Bank defines vulnerability to poverty as the probability or risk of becoming poor or falling deeper into poverty in the future. The National Team for the Acceleration of Poverty Reduction

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reports that approximately 40% of the total population belongs to the vulnerable poor group14. Poverty vulnerability has future implications; thus, this research is crucial for formulating government policies for the vulnerable population to prevent them from falling into poverty.

A household's descent into poverty is influenced by various factors, originating both from within and outside the household, as well as from social, economic, and demographic aspects. Shocks in the economy, climate, natural conditions, social environment, or other adverse conditions can cause households to become poor in the coming period17. Income shocks have varying impacts on household welfare. Prosperous households can cope with income shocks, thereby avoiding poverty. However, households lacking adequate capacity will experience vulnerability to poverty. This condition is commonly found in underdeveloped regions.

According to Chaudhuri et al. (2002), poverty and vulnerability to poverty are two sides of the same coin; the poverty rate is the ex-post realization of a random variable, whereas poverty vulnerability is the ex-ante expectation of the household. The Central Statistics Agency (BPS) delimits the determination of very vulnerable, vulnerable, and near-vulnerable based on welfare status using the poverty lin. The population is categorized as vulnerable if their per capita expenditure falls within the range of the poverty line to 1.6 times the poverty line (Priastiwi, 2023). BPS reports indicate that poor households tend to be characterized by a larger average number of household members, older age, female household heads, low education, and employment in the agricultural sector.

In addition to asset ownership, BPS states that criteria for poor households include having unprotected springs as the main source of drinking water and non-electric lighting sources; these indicators reflect basic infrastructure conditions and access to essential services directly related to daily quality of life (Sa'diyah & Arianti, 2012). According to Tulit (2022) regional poverty can decrease economic growth. Increased economic growth in a region impacts the improvement of community welfare, thereby reducing poverty. Unemployment has a detrimental effect on the prosperity achieved by an individual or household (Anggraini et al., 2023). Community welfare declines with unemployment, which naturally increases the probability of falling into poverty due to a lack of income. Low income reduces household welfare levels and increases the percentage of poverty in a region.

The literature review on poverty and poverty vulnerability demonstrates a diverse array of multidimensional determinants, encompassing individual characteristics, household attributes, and external factors. At the micro-level, prior studies Sa'diyah & Arianti (2012) consistently identify educational attainment, asset ownership, and household size as crucial factors determining a family's economic status. Meanwhile, at the regional level, economic growth and the Human Development Index (HDI) have been proven to have a significant negative correlation with poverty levels (Ardian et al., 2021). However, studies focusing on poverty vulnerability (Priastiwi, 2023; Riantini et al., 2019) introduce a new dimension by highlighting the role of external shocks—such as climate change, weather variability, and geographical location—which can accelerate the transition of households from non-poor to vulnerable categories. Although several studies indicate varying levels of vulnerability across different regions in Indonesia (Rahman & Wulansari, 2018; Adnyani & Sugiharti, 2019), there is an academic consensus that effective policy interventions require the integration of human resource capacity building with protection against environmental and economic shocks.

Previous studies have examined poverty vulnerability at the household level and in specific regional settings, including East Nusa Tenggara (Priastiwi, 2023). This study differs by examining 26 officially designated underdeveloped districts across Indonesia using cross-sectional data for 2023 and by integrating macroeconomic indicators with district-level aggregates of household living-condition indicators. Accordingly, the contribution of this study is comparative and classificatory rather than longitudinal; it does not assess post-pandemic changes over the 2017-2022 period.

The objective of this study is to determine the level of poverty vulnerability in underdeveloped regions and identify the determinant factors that contribute to poverty vulnerability in these areas.

RESEARCH METHOD

This study uses cross-sectional data from 2023. The observation units are districts designated as underdeveloped regions in Indonesia. Presidential Regulation No. 63 of 2020 identifies 62 underdeveloped districts, of which 26 districts are included in this study based on the availability of complete data. The study therefore uses a data-availability sample rather than a probability sample. Secondary data were obtained from the Indonesian Central Bureau of Statistics (BPS), and the results are interpreted with reference to the 26 sampled districts.

Poverty-vulnerability group status is used as the dependent variable. The macroeconomic approach consists of population density, economic growth, and the open unemployment rate. The micro-oriented indicators represent household living conditions aggregated at district level and consist of rental or contract housing status, unprotected drinking-water sources, and non-electric lighting. These six indicators are used as predictor variables in the discriminant analysis.

Discriminant analysis is a multivariate classification technique used to examine whether a set of predictors can distinguish predefined groups and to construct a discriminant function for group classification. In linear discriminant analysis, the function is formed as a linear combination of predictor variables that maximizes between-group variation relative to within-group variation. Because the dependent variable in this study contains two predefined groups, only one discriminant function can be extracted. Standard considerations include independence of observations, multivariate normality within groups, and homogeneity of covariance matrices (Chen & Jiang, 2018 ; Aisyah, 2023).

The Linear Discriminant Function is calculated using a linear combination of predictor variables, written as:

$$Di = \omega 1X1 + \omega 2X2 + \cdots + \omega kXk + c$$

Where:

Di	: discriminant value for group i
$X1, X2, Xk$	: predictor variable
$\omega 1, \omega 2, \omega k$	: coefficient or weight obtained from the analysis
c	: constanta.

The coefficients $\omega 1, \omega 2, \dots, \omega k$ are calculated based on analysis of variance between groups and within groups, with the aim of maximising the ratio of variance between groups to variance within groups.

To test the assumptions before applying the discriminant function. Once the assumptions have been tested and confirmed to be valid, the next step is to calculate the discriminant function. This function is usually expressed in linear form, which can be used to classify new data into predetermined groups. The performance of the discriminant function can be tested using cross-validation techniques, where the data is divided into several subsets to test the accuracy of the model (Zahruddin et al., 2023; Rohman et al., 2022). This method allows researchers to evaluate how well the discriminant function can classify previously unseen data.

Model evaluation is conducted to assess the effectiveness and accuracy of the model in differentiating groups based on independent variables, using tests such as Wilk's Lambda, Univariate Test, Group Difference Evaluation (Centroid), and Classification Matrix (Confusion Matrix).

Wilk's Lambda test is used to evaluate the significance of the discriminant function as a whole and to test whether there are significant differences between the groups being tested. A small Wilk's Lambda value indicates that the discriminant model can distinguish between groups well. If the significance value (p value) is less than 0.05, then the discriminant function is considered significant. Univariate tests are conducted to assess the significance of each independent variable in the discriminant function. This helps identify the most influential variables in distinguishing between groups.

The next test is the evaluation of group differences (Centroid). Centroid is the average discriminant score for each group. The distance between group centroids shows the extent to which the groups can be distinguished by the discriminant function. The greater the difference in centroids, the better the model is at separating groups.

After the discriminant function is calculated, the data is classified based on the calculated discriminant function value. If the discriminant function value is higher for one group than another, the individual or observation will be classified into the group with the highest discriminant value. Everyone will be predicted into a particular group based on the previously calculated discriminant function. For example, if the discriminant function for group A is higher than group B, then the individual will be classified into group A.

RESULTS AND DISCUSSION

Poverty vulnerability is a complex and multidimensional issue faced by many communities in Indonesia. Poverty vulnerability can be understood as a condition in which individuals or groups are at high risk of falling into poverty or experiencing deeper poverty due to various external and internal factors.

Poverty vulnerability can be defined as the risk faced by individuals or groups of falling into poverty in the future. This is often related to economic uncertainty, access to resources, and the ability to cope with external shocks, such as natural disasters or economic crises (Elanda & Alie, 2023). According to Chambers, there are five interrelated elements in the poverty trap, namely poverty itself, isolation, physical weakness, powerlessness, and vulnerability (As-Sadili et al., 2023). These elements show how individuals or groups can be trapped in a cycle of poverty that is difficult to break. Several factors causing poverty vulnerability in Indonesia, particularly in underdeveloped regions, are unequal economic growth, low education levels, limited access to resources, and poor environmental conditions.

Uneven economic growth across Indonesia has led to significant income disparities. This has resulted in some regions experiencing more severe poverty than other more developed regions (Rani et al., 2020). This inequality hinders poor communities' access to better economic opportunities. Low levels of education often prevent individuals from obtaining decent jobs. Research shows that low levels of education contribute to vulnerability to poverty, as individuals with low levels of education tend to have fewer skills and find it difficult to compete in the job market (As-Sadili et al., 2023).

Communities living in remote or underdeveloped areas often have limited access to resources such as capital, infrastructure, and basic services. This makes them more vulnerable to economic and social shocks (Rahman & Wulansari, 2018). Communities living in areas with poor environmental conditions, such as coastal areas vulnerable to climate change, also experience higher vulnerability.

In this study, 26 regencies (kabupaten) were analyzed from the population of 62 districts designated as underdeveloped regions under Presidential Regulation No. 63 of 2020. The sample was determined by the availability of complete data for the study variables. The following description therefore refers to the 26 sampled regencies.

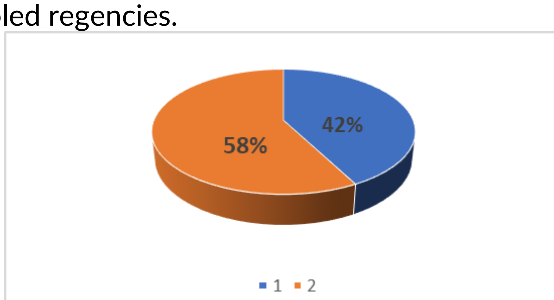

Figure 1. Percentage of areas vulnerable to poverty in 2023
Source: Excel

Almost half (42%) are in a state of poverty vulnerability. This value is substantial; without improvements in influencing factors, most underdeveloped regions will fall into poverty annually.

Regions classified as underdeveloped region often exhibit high vulnerability to poverty. This can be explained by various interacting factors, including poor infrastructure, limited access to basic services, and economic instability. Research shows that di underdeveloped region often lacks adequate regulations and the capacity to meet the needs of their communities, which contributes to their lag more developed regions (Fernandes et al., 2023).

Poor infrastructure conditions in underdeveloped region have a significant impact on poverty levels. For example, Iskandar (2019) emphasises that the uneven implementation of regional autonomy can lead to disparities in development achievements, which in turn contribute to increased poverty levels. The inability of local governments to respond to the needs of communities in underdeveloped region often results in a lack of investment in infrastructure and public services, which are essential for improving quality of life and reducing poverty (Iskandar, 2019).

Furthermore, economic instability in underdeveloped regions is also a significant factor contributing to vulnerability to poverty. Research by Kabbaro et al. (2016) shows that unstable economic conditions, such as income fluctuations due to dependence on the agricultural sector, which is vulnerable to climate change, can exacerbate poverty in these regions. Families dependent on agriculture often face significant challenges, such as natural disasters that threaten their crops and incomes (Kabbaro et al., 2016).

Access to safe drinking water and adequate lighting are crucial factors in determining a region's poverty status, particularly in underdeveloped areas. Areas lacking adequate access to clean water and lighting often experience a variety of health and social problems that contribute to poverty. Research shows that poor water quality can cause various diseases, such as diarrhea, which directly impact public health and economic productivity (Hidayah et al., 2021; Anggraini et al., 2023). The availability of safe, clean water is crucial for public health. According to Djaja et al. (2022), better access to drinking water and sanitation contributes to improved public health, which in turn can reduce poverty levels. When people lack access to clean water, they are more vulnerable to infectious diseases that can interfere with their ability to work and produce, thus worsening their economic conditions (Djaja et al., 2022). Furthermore, research by Hidayah et al. (2021) shows that the presence of pathogenic bacteria in drinking water can cause serious illnesses, especially in children, which increases mortality rates and reduces quality of life.

Adequate lighting also plays a crucial role in supporting economic and educational activities. In underdeveloped areas, lack of access to electricity can limit children's learning time and reduce adult work productivity, ultimately contributing to the cycle of poverty (Hutasoit & Sinaga, 2023). Research by Jannah & Muchlisoh (2019) emphasizes that access to safe drinking water and adequate lighting are human rights and essential for achieving sustainable development goals.

Furthermore, poor access to clean water and sanitation can worsen a community's socioeconomic conditions. Research shows that families without access to improved water sources have a higher risk of stunting in their children, an indicator of poverty and poor health (Astuti, 2022; Olo et al., 2021). This suggests that interventions to improve access to clean water and sanitation must be implemented simultaneously to achieve better results in poverty alleviation (Astuti, 2022; Agustia & Rosyada, 2023).

Disparities in access to education and healthcare also contribute to the cycle of poverty in underdeveloped regions. Research by F. A. Rohman (2023) shows that disparities in environmental quality and access to healthcare can worsen socioeconomic conditions. This creates a vicious cycle where a lack of education and good healthcare hinders job opportunities and better incomes, thus perpetuating poverty in the region.

Discriminant Model

Table 1. Eigenvalues and Wilks'Lambda

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.145a	100.0	100.0	.356

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	Df	Sig.
1	.873	2,846	6	.828

Source: Authors' calculations based on BPS data (2023)

The eigenvalue of the discriminant function is 0.145, indicating limited separation between the two groups. Because the analysis contains only two groups, a maximum of one discriminant function can be extracted.

The reported 100.0% of variance refers to the proportion of discriminant variance accounted for by the single available function. It should not be interpreted as meaning that the function explains 100% of the variability in the original predictor data.

The canonical correlation is 0.356, indicating a weak association between the discriminant scores and group membership. Squaring the canonical correlation gives approximately 0.127, which further suggests that the separation captured by the function is limited.

Wilks' Lambda is 0.873, with $\chi^2 = 2.846$, df = 6, and p = 0.828. Because the significance value is greater than 0.05, the discriminant function is not statistically significant. Thus, the six predictor variables do not jointly provide statistically reliable evidence of separation between the vulnerable and non-vulnerable groups in this sample. The subsequent coefficients and structure loadings should therefore be interpreted as exploratory descriptions rather than as statistically confirmed determinants.

Interpretation of Discriminant Function Coefficients

The standardized coefficients indicate how much influence each variable has on the discriminant function. The larger the coefficient, the greater the variable's contribution to differentiating the groups.

Table 2. Standardized Canonical Discriminant Function Coefficients

Variable	Function 1
Rent	.607
Drinking water	.042
Electricity	.538
Economic Growth (PE)	.660
Open Unemployment Rate (TPT)	.464
Population Density (KP)	.743

Source: Eviews

The "Rent" variable has a positive coefficient of 0.607, indicating that the greater the value of "Rent", the greater its contribution to the separation between the groups analyzed. The "Drinking" variable has a very small coefficient of 0.042, indicating that this variable contributes almost nothing in differentiating the groups. The "Electricity" variable has a positive coefficient of 0.538, indicating that "Electricity" contributes to differentiating the groups, although its influence is smaller than "Rent". The "PE" variable has a coefficient of 0.660, indicating that this variable has a moderate influence in differentiating the groups, greater than other variables such as "Electricity" or "Rent". The "TPT" variable with a coefficient of 0.464 shows a moderate influence in differentiating the groups. The "KP" variable has a coefficient of 0.743, which is the highest coefficient among the other variables. This indicates that "KP" has the greatest influence in differentiating the groups.

These coefficients indicate the relative contribution of each variable to the discriminant function. A larger value indicates a more important variable in differentiating the groups. In this case, the variable with the largest influence is KP (0.743), followed by PE (0.660) and Rent (0.607). Conversely, the variable Drinking (0.042) has a very small influence, meaning it does not make a significant contribution to differentiating the groups.

Since all the coefficients are positive, it can be concluded that an increase in the value of each variable (Rent, Electricity, PE, TPT, KP) will contribute to the separation between groups in the same direction. Variables with larger coefficients indicate a more dominant role in distinguishing groups.

Structure Matrix

The Structure Matrix in discriminant analysis, which shows the correlation between the discriminant variables and the standardized canonical discriminant function. It provides information on how much each variable contributes to the discriminant function, as well as the extent to which those variables are correlated with the discriminant function.

The correlation values given in this matrix indicate the strength of the relationship between each variable (e.g., KP, Electricity, Rent, etc.) and the first discriminant function. A higher correlation indicates that the variable is more closely related to the discriminant function and is more important in distinguishing groups.

Table 3. Structure Matrix

Variable	Function 1
Population Density (KP)	.638
Electricity	.304
Rent	.299
Economic Growth (PE)	.162
Open Unemployment Rate (TPT)	.149
Drinking Water	.130

Source: Eviews

The Structure Matrix in discriminant analysis, which shows the correlation between the discriminant variables and the standardized canonical discriminant function. It provides information on how much each variable contributes to the discriminant function, as well as the extent to which those variables are correlated with the discriminant function.

The correlation values given in this matrix indicate the strength of the relationship between each variable (e.g., KP, Electricity, Rent, etc.) and the first discriminant function. A higher correlation indicates that the variable is more closely related to the discriminant function and is more important in distinguishing groups.

The variable "KP" has the highest correlation with the first discriminant function (0.638), indicating that "KP" is the most influential variable in distinguishing groups in the data. The variable "Electricity" has a moderate correlation with the discriminant function (0.304), indicating a smaller contribution compared to "KP", but still quite significant. The correlation of the variable "Rent" with the discriminant function is 0.299, which is slightly smaller than "Electricity". However, "Rent" still plays a role in distinguishing groups. The correlation of the variable "PE" with the discriminant function is 0.162, indicating a smaller influence compared to the other variables. The correlation for the variable "TPT" is 0.149, indicating an even smaller contribution in distinguishing groups. The variable "Drinking" has the lowest correlation with the discriminant function (0.130), indicating that "Drinking" makes the smallest contribution in distinguishing groups.

"KP" is the variable with the highest correlation, meaning that "KP" is the most important variable in distinguishing groups based on the first discriminant function. This also means that this variable is very important in the analysis. Electricity (0.304) and Rent (0.299) show more moderate correlations, meaning that they also contribute quite significantly, but not as much as "KP". The variables Drinking (0.130) and TPT (0.149) show very low correlations with the discriminant function, meaning that they contribute very little to distinguishing groups in the data. PE (0.162) also has a relatively small contribution.

Discussion

The discriminant analysis revealed several key findings related to the variables influencing the segregation between vulnerable and non-poor districts. These findings provide valuable insights into the factors contributing to poverty in these areas. The variable "rental housing" indicates that the higher the rental value, the greater its contribution to the segregation between vulnerable and non-poor districts. This aligns with research showing that inadequate housing conditions can contribute to higher poverty rates, as high rents can reduce the income available for other basic needs (Alfina, 2023; Darmawanto et al., 2023). High rent costs often prevent families from allocating funds for basic needs such as education, healthcare, or other productive investments. In a policy context, it is important to encourage affordable housing development programs, especially in areas with high poverty rates. The government can also consider housing subsidies or incentives for developers who build affordable housing. Furthermore, improving spatial planning regulations to prevent land price speculation could help reduce housing costs. Further studies could focus on how housing expenditures affect the consumption patterns of poor communities in specific areas.

The findings indicate that the higher the "rent" value, the greater its contribution to the disparity between vulnerable and low-poverty districts. This can be explained by the fact that high rents often reflect better economic conditions, but they can also be a burden for low-income individuals or families. In this context, expensive rental housing may indicate that individuals or families may have to sacrifice spending on other basic needs, such as food and education, which in turn can exacerbate their poverty situation. Previous research also shows that access to affordable housing is crucial for poverty reduction. When rents rise, low-income individuals may be forced to live in less healthy or unsafe environments, which can worsen their social and economic conditions. Therefore, this variable is highly relevant in the discriminant analysis. The variable "access to drinking water sources" contributes little to the separation between districts vulnerable to poverty and those not. Previous research suggests that while access to clean water is important for health, in certain contexts, this variable may not have a significant impact on poverty status, especially when other factors such as education and employment are more prominent (Rakhmawan & Aji, 2023).

Although this variable does not significantly contribute to distinguishing districts vulnerable to poverty, it is important to consider that clean water is a basic need that has an indirect impact on community well-being. Access to clean water may be widespread in the areas analyzed, making its impact on group segregation less visible. However, further research could explore whether water quality, the cost of access, or the stability of the water supply impact community well-being. Related policies could focus on providing free or affordable clean water in areas with vulnerable populations, given its significant impact on public health and economic productivity.

The finding that "access to drinking water sources" contributes little to the disparity between vulnerable and poor districts does not indicate that, although access to clean water is crucial for health, in certain contexts, this variable may not have a significant impact on poverty status. Research shows that access to clean water is important, but other factors such as education, employment, and income are often more dominant in determining poverty status. In some cases, even with access to clean water, individuals or families may still face greater economic challenges that impact their ability to meet other basic needs. Therefore, while clean water access is an important factor, its impact on the gap between vulnerable and vulnerable districts may not be as strong as other variables.

The variable "access to electricity" appears to contribute to group differentiation, although its effect is smaller than that of "rented housing." Access to electricity is often associated with improved quality of life and economic opportunities, but its impact can vary depending on local context and other contributing factors (Istiqomah et al., 2024). This variable demonstrates a moderating effect in differentiating groups. Electricity access is often an early indicator of broader infrastructure development, such as internet access, technology-based education, and new economic opportunities. It is important to analyze whether the limitations of electricity access in poverty-prone districts are geographic (e.g., remote areas) or economic (e.g., too high costs). Possible policies include electricity tariff subsidies, promoting more affordable renewable energy, or providing off-grid electricity networks for remote areas. Furthermore, electricity infrastructure can be combined with other programs, such as technology-based skills training, to accelerate its impact on community economic development.

The variable "economic growth" has a significant influence in distinguishing between districts vulnerable to poverty and those not. Research shows that positive economic growth can reduce poverty levels by creating more jobs and increasing community income (Hanifah & Hanifa, 2021; Ratih Primandari, 2019). This suggests that policies supporting economic growth can be an effective strategy for poverty reduction. The significant influence of this variable underscore the importance of policies that promote inclusive economic growth. Unequal economic growth often leaves certain groups in poverty. Therefore, policies must be designed not only to boost economic growth but also to ensure that its benefits are felt by all levels of society. Programs such as developing MSMEs, increasing access to capital for smallholder farmers, or investing in labor intensive sectors can help create more jobs. Furthermore, the government can encourage local economic development through strategies such as industrial clusters based on local resources or potential in vulnerable areas.

The "open unemployment rate" variable shows a moderate effect in distinguishing between districts vulnerable to poverty and those not. High unemployment rates are often associated with poverty, as unemployed individuals tend to have low incomes and struggle to meet basic needs. Research shows that unemployment can exacerbate social and economic conditions, creating a cycle of poverty that is difficult to break. However, the impact of unemployment rates may vary depending on the local context. In some areas, despite high unemployment rates, individuals may have access to other resources that can help them survive, such as social support or government programs. Therefore, while unemployment contributes to poverty, its impact may not always be immediately visible in the separation between vulnerable and non-poor districts.

The variable "population density" has the greatest influence in distinguishing between vulnerable and non-poor districts. Research shows that high population density can lead to increased competition for resources, jobs, and services, which in turn can increase poverty levels in these areas (Adam et al., 2022). Overall, these findings suggest that a combination of factors, including housing conditions, access to basic services, economic growth, and unemployment rates, contribute to the disparity between vulnerable and non-poor districts. Therefore, interventions targeting housing improvements, job creation, and increased access to basic services could be important steps in reducing poverty in these areas.

The significant influence of this variable highlights the importance of population density management to reduce pressure on resources. Policies that promote economic decentralization can help reduce the burden on large cities or densely populated areas. For example, encouraging the development of new economic centers in less developed areas can create job opportunities and reduce over-urbanization. Furthermore, effective family planning programs can help manage population growth, especially in areas with high poverty rates. Further studies could also focus on how the management of public spaces and infrastructure in densely populated areas affects community well-being.

CONCLUSION

Underdeveloped areas are very vulnerable to falling into poverty. If there is no improvement in the factors that influence it, most underdeveloped areas will fall into poverty.

The variable "rental residence" shows that the greater the value of "Rent", the more it contributes to the separation between vulnerable and non-poor districts. The variable "access to drinking water sources" shows that this variable almost does not contribute to the separation between vulnerable and non-poor districts. The variable "access to electricity" shows that "access to electricity" contributes to differentiating groups, although its influence is smaller than "rental residence".

The variable "Economic growth" shows that this variable has quite an influence in differentiating between vulnerable and non-poor districts, greater than other variables. The variable "Open unemployment rate" shows a moderate influence in differentiating between vulnerable and non-poor districts. The variable "Population density" has the greatest influence in differentiating between vulnerable and non-poor districts

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