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ANALYTICAL APPROACH OF GENERALIZED LINEAR MODELS FOR HANDLING OVERDISPERSION IN POVERTY DATA OF INDONESIA

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ABSTRACT

Poverty is one of the complex phenomena that occurs in Indonesia. Various socio-economic variables in Indonesia influence poverty, which we can mathematically model using the Generalized Linear Model (GLM) framework. In this study, we modeled data on the number of poor people per province in 2023 taken from the Badan Pusat Statistik of Indonesia website. The response variable in this study was initially assumed to exhibit equidispersion, where the variance equals the mean. However, the observed variance exceeded the mean, indicating overdispersion. Consequently, Negative Binomial Regression, an extension of the GLM that introduces an additional dispersion parameter, was applied to account for this overdispersion. This approach accommodates overdispersed count data by incorporating a gamma-distributed latent variable. The aim of this study is to determine the best model using Negative Binomial Regression in handling overdispersion in Indonesia's poverty data. This model was chosen for its robustness in capturing increased data variability, enabling the identification of factors that influence poverty. The results of this study offer a mathematically rigorous approach to better understand the underlying dynamics of poverty across provinces in Indonesia.

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1. INTRODUCTION

Indonesia, as a developing country, is certainly facing various problems, one of the problems that the government and society have been focusing on for a long time is poverty [1]. Poverty is the lack of goods and services needed to achieve a decent standard of living [14]. The Badan Pusat Statistik (BPS) found that as of March 2021, there were 27.54 million Indonesians who were below the poverty line until the first quarter of 2021 using the income threshold indicator of IDR 472,525 per capita per month [2]. Ironically, Indonesia has not been free from extreme poverty until now, where the position of extreme poverty rate as of March 2022 is 2.04% [3]. A person is classified as extremely poor if the cost of daily living needs is below the extreme poverty line or equivalent to USD 1.9 Purchasing Power Parity (PPP) [4].

The high poverty rate in Indonesia affects many negative things in life, such as the increase in unemployment rate, the number of school dropouts, health problems in the community, the increase in criminal acts, the increase in mortality rate, and various conflicts that occur in the community will emerge [5]. This condition shows the urgency of identifying and understanding the factors that cause it, this has also been the focus of various previous studies in the analysis of the factors or indicators that cause it. Previous research has been conducted to analyze the effect of human development index (HDI), consumption, investment, and provincial minimum wage on poverty in Indonesia in 2020 [6]. Then, another study examined the correlation between HDI, inflation, and unemployment with poverty in Indonesia [7]. Based on the data processed by the BPS in the last 3 years, these factors have increased, but the poverty rate in Indonesia in the last 3 years has not always decreased [12]. The novelty of this study lies in the updated data and the use of a different method from previous research, namely the negative binomial regression method. Based on the data processed by the Central Statistics Agency (BPS) in the last 3 years, HDI, provincial minimum wage and domestic investment realization, but the poverty rate in Indonesia in the last 3 years has not always decreased [12].Therefore, further research will be conducted on the factors that influence the decline/increase of poverty in Indonesia with a target poverty rate of 6.5 - 7.5 percent by 2024.

The inadequate quality of human resources is one of the factors in the low community productivity, which in turn leads to low income. This phenomenon highlights that the quality of human resources is a root cause of poverty [8]. The achievement of human quality of life development can be measured by an indicator called the HDI). Additionally, the level of wages is another critical factor influencing poverty, as wages serve as a primary source of income. If income stagnates or declines, it directly impacts welfare [15]. In Indonesia, the provincial minimum wage (UMP), set by the governor, serves as a benchmark for labor wages in the region and acts as a minimum standard to ensure that workers' wages reflect the feasibility and align with the quality of life in the province [9]. Together, these factors underscore the interconnectedness of human resource quality, wages, and poverty.

In the Harrod-Domar theory, there is a favorable influence between investment activities on a country's economic growth process [10]. The formation of capital is viewed as an expenditure that will increase an economy's capacity to produce goods as well as an expenditure that will enhance the effective demand of the entire society. The core of the Harrod-Domar theory is that every economy can set aside a portion of its national income to replace depreciated capital goods (such as buildings, equipment, and materials). However, to achieve economic growth, additional investments are required to increase the overall stock of capital. [31]. Investment can be a major contributor to the development of a region as well as a solution to the government's limitations in facilitating funds for development. Investment activities allow a society to continuously increase economic activity and employment opportunities, increase national income and increase the level of prosperity of the community [16].

Previous studies have examined several variables related to tuberculosis using the Negative Binomial Model, similar to the current research. In that study, comparisons were made between several models, including the normal distribution model, Poisson distribution, and Negative Binomial distribution. It was found that the Negative Binomial distribution could adequately explain the number of tuberculosis cases. Therefore, this study employs the Negative Binomial regression model as the analytical method, given that Indonesia's poverty data exhibits overdispersion characteristics, making it well-suited to the model's assumptions [30].

This study adopts the best method validated by previous research, which is Negative Binomial Regression, to analyze the relationship between the HDI, provincial minimum wage, and investment on poverty in Indonesia in 2023 [13]. This study further contributes by utilizing the latest available data, providing more current insights into these variables effects on poverty. The purpose of this study is to obtain the best regression model obtained from Negative Binomial Regression analysis results based on Akaike's Information Criterion (AIC) criteria, which will obtain which factors can significantly affect the case of the number of poor people by province in Indonesia in 2023. The use of Negative Binomial Regression is motivated by the presence of overdispersion in the data, where the variance exceeds the mean. This is necessary so that preventive measures against poverty can be implemented and special policy approaches can be carried out through various programs to be implemented by ministries or local government agencies.

2. RESEARCH METHODS

2.1 Research Data and Variables

In this study, the data obtained is secondary data obtained from the website Badan Pusat Statistik and Ministry of Labor. The data consists of 34 provinces in Indonesia equipped with 1 dependent variable, namely the number of poor people by province (in thousand people) [32], and 3 independent variables, namely the HDI [33], the provincial minimum wage (in rupiah) [34], and the realization of domestic investment (in billion rupiah) [35]. Below is data on the number of poor people by province in Indonesia in 2023:

Table 1. Number of Poor People and its Influencing Factors by Province in Indonesia in 2023

Province	Number of Poor People by Province (Thousand Population)	Human Development Index (%)	Provincial Minimum Wage (IDR)	Domestic Investment Realization (IDR)
Aceh	807	74.70	3413666.00	4424.2
Sumatera Utara	1240	75.13	2710493.93	22789.2
Sumatera Barat	340	75.64	2742476.00	2559.8
Riau	486	74.95	3191662.53	43062
Jambi	281	73.73	2943033.08	8882.7
…	…	…	…	...
Papua Barat	215	67.47	3282000.00	2139.1
Papua	915	63.01	3864696.00	1311.8

Data source: *Badan Pusat Statistik*

2.2 Descriptive Analysis

Descriptive analysis is one of the research methods used to display, compile, or summarize the collected data in order to provide an overview of the existing problems without the intention of making general conclusions or generalizations, using measures such as median, standard deviation, minimum, maximum, and mean values to facilitate a better understanding of the data [17]. Usually, the data collected is presented in the form of tables, graphs, charts, data centering measures, data distribution measures, and others.

2.3 Multicollinearity

The existence of a relationship between predictor variables or X is called a multicollinearity event. In the regression model, the presence or absence of multicollinearity can be seen using the Variance Inflation Factor (VIF) value [22]. The VIF value can be expressed as follows:

$$VIF = \frac{1}{\left(1 - R_j^2\right)} \tag{1}$$

Where $j = 1, 2, \ldots, p$, p is the number of variables, and R_j^2 is the coefficient of determination of the variable X_j with other predictor variables [22], that is:

$$R_j^2 = \frac{Sum\ Square\ Regression}{Total\ Sum\ Square} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{p}\left(\hat{Y}_{ij} - \underline{Y_{ij}}\right)}{\sum_{i=1}^{n}\sum_{j=1}^{p}\left(Y_{ij} - \underline{Y_{ij}}\right)^2} \tag{2}$$

If the VIF value is less than or equal to 10, then there is no multicollinearity event in the regression model, which means there is no relationship between the predictor variables or X.

2.4 Equidispersion Assumption Testing

When the equidispersion assumption is violated due to overdispersion, Negative Binomial Regression can be applied to handle the issue by introducing an additional dispersion parameter [21]. Equidispersion is a condition when the mean value of the response variable or Y is equal to the variance value. $\left(E(y_i) = Var(y_i)\right)$. However, in reality, this assumption is often violated. Violation of the equidispersion assumption is divided into two conditions, namely overdispersion and underdispersion. Overdispersion occurs when the variance value is greater than the average value. $\left(Var(y_i) > E(y_i)\right)$. Where as underdispersion occurs when the variance value is smaller than the mean value $\left(Var(y_i) < E(y_i)\right)$.

As a result, if the PR model is applied to data with overdispersion or underdispersion, the standard error of the regression coefficient may be overestimated or underestimated, leading to errors in hypothesis testing and causing the conclusions to become inconsistent and potentially invalid [21]. Dispersion parameter (δ) can be calculated with the following formula.

$$\delta = \frac{Deviance}{db} \tag{3}$$

Where $db = n - k - 1$. Deviance is defined as follows:

$$Deviance = 2\sum_{i=1}^{n}\left\{y_i ln\left(\frac{y_i}{\mu_i}\right) - (y_i - \mu_i)\right\} \tag{4}$$

If the value of the dispersion parameter (δ) has a value greater than one, then there is overdispersion in the data. Conversely, if the value of the dispersion parameter (δ) has a value less than one, then there is underdispersion in the data.

2.5 Negative Binomial Distribution

The Negative Binomial Distribution is a distribution with many ways in the process of deriving it. In this research, the negative binomial distribution will be used as a Poisson-Gamma mixture [25].

According to [26], the negative binomial distribution is expressed as follows:

$$f(y;\ \mu,\alpha) = \frac{\Gamma\left(y_i + \frac{1}{\alpha}\right)}{\Gamma(y_i + 1)\Gamma\left(\frac{1}{\alpha}\right)}\left(\frac{1}{1 + \alpha\mu}\right)^{\frac{1}{\alpha}}\left(1 - \frac{1}{1 + \alpha\mu}\right)^{y_i} \tag{5}$$

The negative Binomial distribution has a mean μ and variance $\mu + \alpha\mu^2$ [26].

2.6 Negative Binomial Regression

Negative binomial regression is a model with a negative binomial distribution to model count data that experiences a condition of overdispersion or equidispersion [27].

Negative binomial regression uses a GLM model whose log link function is assumed to be of the following form:

$$Y = log\, \mu = n = x'\beta \tag{6}$$

Parameter estimation $\beta_0, \beta_1, \beta_2, \ldots.., \beta_{k-1}, \beta_k$ using MLE. Likelihood function $L(\mu, y, \alpha)$ of the negative binomial distribution equation can be expressed as follows [26].

$$L(\mu,\alpha) = \prod_{i=1}^{n}\left[\frac{\Gamma\left(y_i + \frac{1}{\alpha}\right)}{\Gamma(y_i + 1)\Gamma\left(\frac{1}{\alpha}\right)}\left(\frac{1}{1 + \alpha\mu_i}\right)^{\frac{1}{\alpha}}\left(\frac{\alpha\mu_i}{1 + \alpha\mu_i}\right)^{y_i}\right] \tag{7}$$

The negative binomial regression likelihood function can be simplified, to simplify the function will be done by finding the log likelihood function of the function.

$$l(\mu,\alpha)=\sum_{i=1}^{n}\left[log\Gamma\left(y_i+\frac{1}{\alpha}\right)-log\Gamma(y_i+1)-log\Gamma\left(\frac{1}{\alpha}\right)+\frac{1}{\alpha}log\left(\frac{1}{1+\alpha\mu_i}\right)+y_i log\left(\frac{\alpha\mu_i}{1+\alpha\mu_i}\right)\right] \quad (8)$$

Parameter estimation in negative binomial regression can use iteratively reweighted least squares (IRLS). The IRLS method is known as the Fisher Scoring method [26].

2.7 Model Parameter Significance Test

Model parameter testing is carried out simultaneously and partially to determine whether the model obtained is suitable for use or not. Simultaneous testing is carried out to determine the effect of predictor variables or X as a whole on the response variable or Y with a certain level of significance. While partial parameter testing is carried out to determine whether or not there is a significant effect or influence of each X variable on the response variable or Y [19]. Simultaneous testing on the model is done with the likelihood ratio test statistic.

Hypothesis:

$H_0: \beta_1 = \beta_2 = \ldots = \beta_p = 0$

(The predictor variable or X as a whole has no effect on the response variable or Y)

H_1: There is at least one $\beta_j \neq 0$

(At least one predictor variable or X as a whole affects the response variable or Y)

Statistics Test:

$$G = -2(L_{reduce} - L_{Full}) \quad (9)$$

Where L_{reduce} is the estimated value of the log likelihood function after the substitution process of the estimated value of parameter 0 obtained from the estimated $log(\mu_i) = \beta_0$ (model with intercept only). While L_{Full} is the estimated value of the log likelihood function after the substitution process of the estimated parameter values $\beta_0, \beta_1, \ldots, \beta_j$ obtained from the estimation of the overall model.

If the value of $G > \chi^2_{(\alpha;p)}$ with p is k parameters of the overall model minus k parameters of the reduced model, then H_0 is rejected, which means that there is one predictor variable or X that has a significant effect on the model so that it continues with partial testing with the Z test.

Hypothesis:

$H_0: \beta_j = 0$ (The predictor or j-th X variable has no effect on the response variable or Y)

$H_1: \beta_j \neq 0$ (The predictor or j-th X variable affects the response variable or Y)

Statistics Test:

$$Z = \frac{\hat{\beta}_j}{SE(\hat{\beta}_j)} \quad (10)$$

Where $\hat{\beta}_j$ is parameter estimation from and $SE(\hat{\beta}_j)$ is the estimated standard error of $\hat{\beta}_j$. When $|Z| > Z_{\frac{\alpha}{2}}$, then H_0 is rejected.

2.8 Best Model Criteria

There are several methods that can be used to determine the best model to be used in regression analysis including Akaike Information Criterion (AIC), bootstrap, cross validation, and Bayesian Information Criterion (BIC) [28]. The method generally used to select the best model used is AIC [28].

2.9 Akaike's Information Criterion (AIC)

AIC is defined as follows:

$$AIC = -2(L - K) \quad (11)$$

With L is the log likelihood model and K is the number of parameters used in the model. The model with a smaller AIC value will be chosen as the best model for the data [26]. In this research, a comparison of AIC values will be used to determine the best model to use.

2.10 Research Steps

Here are the research steps.

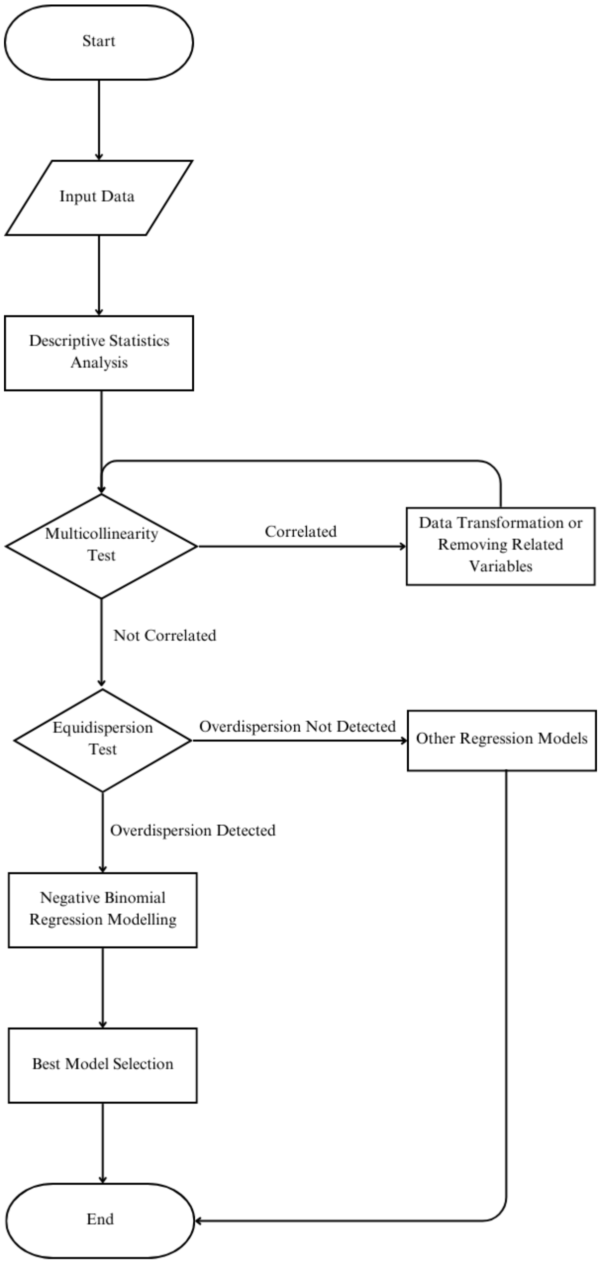

Figure 1. Flowchart

3. RESULTS AND DISCUSSION

All analyses presented in the Results and Discussion section were conducted using the R software.

3.1 Descriptive Statistical Analysis

Descriptive statistics of research data are carried out based on the average value, variance, minimum value, and maximum value. Descriptive statistics of the research subject in the form of the number of poor people and influencing factors based on provinces in Indonesia in 2023 are shown in Table 2.

Table 2. Descriptive Statistical Analysis

Variables	Mean	Variance	Minimum	Maximum
Y	761.2	1,129,967	47.97	4188
X_1	73.77	14.16027	63.01	83.55
X_2	2,923,309	362,541,540,181	1,958,170	4,901,798
X_3	19,779	612,818,413	1,174	95,202

The data distribution indicates a substantial variance in the number of poor people by province in Indonesia in 2023. This suggests that the distribution is highly dispersed, which should be considered when selecting the appropriate method of analysis. Additionally, the provincial minimum wage (X_2) exhibits a wide range, reflecting significant differences across provinces. The high variance in both variables suggests the need to assess whether the assumption of equidispersion is met before proceeding with further analysis.

3.2 Multicollinearity Test

The presence or absence of multicollinearity between predictor variables or X can be seen using the Variance Inflation Factor (VIF) value. The test results get the VIF value as follows:

Table 3. Multicollinearity Testing Results

X_1	X_2	X_3
1.509352	1.032117	1.525282

Since the VIF values on all predictor variables or X are less than 10, it can be concluded that there is no multicollinearity event in the regression model, which means there is no relationship between the predictor variables or X.

3.3 Equidispersion Assumption Testing

The equidispersion assumption states that the mean and variance of the response variable should be approximately equal. Based on the descriptive statistical analysis in Table 2, the mean of Y is 761.2, while its variance is 1,129,967. Since the variance is significantly greater than the mean, this indicates the presence of overdispersion in the data. To address this issue, Negative Binomial Regression is used as it can accommodate overdispersion more effectively.

3.4 Negative Binomial Regression Modeling and Parameter Testing

Negative Binomial Regression analysis is an effective method for handling overdispersion in count data. Using the Maximum Likelihood Estimation (MLE) method, the parameter estimates for the Negative Binomial model are presented in Table 4.

Table 4. Results of Estimation of Negative Binomial Regression Model Parameters

Parameters	Estimator	Estimation	|Z| Score	P-Value
β_0	$\hat{\beta}_0$	65.15	4.69	2.68×10^{-6}
β_1	$\hat{\beta}_1$	-9.24	-3.19	0.00
β_2	$\hat{\beta}_2$	-1.66	-2.76	0.01
β_3	$\hat{\beta}_3$	0.60	4.67	3.05×10^{-6}

From the estimated parameters of the negative binomial regression model, the following model is obtained:

$$\hat{\mu} = exp(65.15 - 9.24x_1 - 1.66x_2 + 0.60x_3)$$

Testing of the Binomial Negative regression model simultaneously performed using the G test with the help of R software, obtained results $P - Value = 3.466 \times 10^{-7} < \alpha = 5\%$, then H_0 is rejected. Then, when you look at the statistics of the G test, you get the results. $G = 32.85 > \chi^2_{(\alpha;p)} = 7.82$, then H_0 is rejected. Thus, with a 5% significance, it can be concluded that there is at least one predictor variable that has a significant influence on the number of poor population by province in Indonesia by 2023. Using the MLE method obtained a partial test result of the negative binomial regression model shown in the table below with an AIC value of 496.28.

Based on the test criteria of the MLE method, when the value $|Z_{hit} > Z_{\alpha/2}|$ then H_0 is rejected or the parameters tested have a significant impact on the number of poor populations by province in Indonesia by 2023. Value $|Z_{hit}|$ of the four parameters greater than $Z_{\alpha/2} = 1.96$ so H_0 is rejected. Then, with 5% significance, P-Value from four parameters is lower then 0.05 so parameters $\beta_0, \beta_1, \beta_2$, and β_3 has a significant impact on the number of poor people per province in Indonesia in 2023.

3.5 Testing the Best Model of Negative Binomial Regression

Based on the partial test, it is found that the three predictor variables or *X* have a significant effect on the response variable or *Y*, so seven possible Negative Binomial regression models are formed and the best Negative Binomial regression model will be found by looking for the smallest AIC value. The following are the AIC values of the seven possible models formed in **Table 5**.

Table 5. AIC Values of Seven Possible Negative Binomial Regression Models

No.	Probability Models	AIC Value	Significant Parameters
1.	x_1	525.10	$\hat{\beta}_0^*, \hat{\beta}_1^*$
2.	x_2	510.41	$\hat{\beta}_0^*, \hat{\beta}_2^*$
3.	x_3	511.59	$\hat{\beta}_0^*, \hat{\beta}_3^*$
4.	x_1, x_2	512.38	$\hat{\beta}_0^*, \hat{\beta}_1^*, \hat{\beta}_2^*$
5.	x_1, x_3	503.88	$\hat{\beta}_0^*, \hat{\beta}_1^*, \hat{\beta}_3^*$
6.	x_2, x_3	505.94	$\hat{\beta}_0^*, \hat{\beta}_2^*, \hat{\beta}_3^*$
7.	x_1, x_2, x_3	*496.28	$\hat{\beta}_0^*, \hat{\beta}_1^*, \hat{\beta}_2^*, \hat{\beta}_3^*$

*Best model

After reviewing the results of checking the AIC values of the seven possible Negative Binomial Regression models, it can be seen that the best model with the smallest AIC value is the model involving three predictor variables, namely the HDI (X_1), provincial minimum wage (X_2), and domestic investment realization (X_3) with an AIC value of 496.28.

Based on the estimation results presented in **Table 5**, the best Negative Binomial Regression model of the data on the number of poor people by province in Indonesia in 2023 is obtained as follows.

$$\hat{\mu} = exp(65.15 - 9.24x_1 - 1.66x_2 + 0.60x_3)$$

3.6 Best Model Selection

Testing the best model is needed to compare which model is better at overcoming overdispersion in the data. The best model selection criterion is AIC where the model chosen is the model with the smallest AIC value.

Table 6. Best Model of Negative Binomial Regression

Models	Significant Variables	AIC
Negative Binomial Regression	x_1, x_2, x_3	496.28

Based on **Table 6**, it can be concluded that the best regression model to overcome the overdispersion case in the PR model of the data on the number of poor people in Indonesia in 2023 is the Negative Binomial model. The Negative Binomial model can be written as follows.

$$\hat{\mu} = exp(65.15 - 9.24x_1 - 1.66x_2 + 0.60x_3)$$

The model above provides information that if x_1, x_2 and x_3 is zero or when there is no provincial minimum wage and domestic investment realization, the average number of poor people is around 18 people with the following details

$$e^{65.15} = 1.97 \; x \; 10^{28}$$

Based on **Table 6**, it was found that the Negative Binomial model is suitable and can be used to address poverty cases in Indonesia. Previous research has also shown that the Negative Binomial model is effective in handling tuberculosis cases. Therefore, it can be concluded that the Negative Binomial model is capable of addressing multiple different cases. For each case, it is essential to determine the most appropriate model, as different cases may require different modeling approaches **[30]**.

4. CONCLUSIONS

The findings suggest that poverty in Indonesia is unevenly distributed across provinces, with significant disparities between regions. The substantial variation in the number of poor people indicates that economic and social conditions may play a crucial role in shaping poverty levels. These results highlight the need for targeted poverty alleviation policies while providing updated insights into the socio-economic factors influencing poverty in Indonesia. To address the overdispersion present in the data, Negative Binomial Regression was used as the analytical model. This model included three variables: human development index, provincial minimum wage, and domestic investment. Model evaluation using the AIC value showed that this model had an AIC of 496.28, indicating its suitability for handling overdispersion in this case.

A key limitation of this research is the analysis is limited to data from a single year, restricting insights into temporal trends. Future studies could benefit from incorporating longitudinal data to provide a more comprehensive understanding of poverty dynamics in Indonesia.

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