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Modeling Poverty Levels in West Java Using Generalized Linear Models with Poisson and Negative Binomial Distributions

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Abstract: *Poverty in West Java Province remains a major challenge with 3.67 million poor people in 2024. This study aims to model the determinants of poverty using the Generalized Linear Model (GLM). This quantitative study uses secondary data from BPS from 27 districts/cities in West Java in 2024 (population census). The instrument is a data extraction sheet with the dependent variable being the number of poor people and independent variables including unemployment, education, GRDP, sanitation, and infant mortality. Analysis techniques include multicollinearity tests, Poisson GLM, Negative Binomial GLM, and model selection based on AIC. The results show that the Negative Binomial model (AIC=305.80) is better than the Poisson (infinite AIC) due to overdispersion. Significant variables are the average length of schooling (β=-0.384, p<0.001) which reduces poverty and infant mortality (β=0.523, p<0.001) which increases poverty. Conclusion: Policy priorities on education and maternal-child health are effective in reducing structural poverty in West Java.*

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Introduction

Poverty is a major social and economic phenomenon that remains a major challenge in Indonesia, particularly in West Java, the most populous province. This condition is characterized by the inability of communities to meet basic needs such as food, clothing, housing, and access to health and sanitation services, which is increasingly complex due to disparities between districts/cities. [Hardinandar, 2019][Buheji et al., 2020]

Although economic growth shows a positive trend, the percentage of poor people in West Java in September 2024 reached around 3.67 million people or 7.97% in 2021, with a significant increase during the pandemic to an additional 999,960 people in 2021. [Kusumawardana, 2022]

The problem of poverty in West Java is influenced by various socio-economic indicators such as the open unemployment rate, labor force participation, Gross Regional Domestic Product (GRDP), proper sanitation, and infant mortality rates, which often show a non-linear relationship to count data such as the number of poor people. [Agustina et al., 2019][Rifkah Nabila, 2021]

These factors cause overdispersion in the data, where classical linear regression is not appropriate, thus requiring a Generalized Linear Model (GLM) approach such as Poisson and Negative Binomial for accurate analysis.[Santi & Rahayuningsih, 2023][Suryadi et al., 2023]

Furthermore, regional inequality and limited access to basic services exacerbate the situation, with the national extreme poverty rate rising to 15.42 million people in 2024, with a similar impact in West Java.[Nurjati, 2021][Safitriani, 2025]

Previous studies on poverty modeling in Indonesia and West Java have generally applied classical regression or descriptive statistical analysis, focusing only on macroeconomic indicators without addressing the problem of data overdispersion in count-type poverty data. Few have combined the Poisson and Negative Binomial models within the Generalized Linear Model (GLM) framework to capture the variability and distribution of poverty across districts and cities. Moreover, existing research often overlooks the integration of socio-economic and demographic variables in a single model that can better reflect the heterogeneous characteristics of regional poverty. This gap highlights the need for a methodological renewal that accommodates overdispersed data to produce more accurate and policy-relevant models for regional poverty alleviation.

This study aims to model the poverty rate in West Java in 2024 using GLM with Poisson and Negative Binomial regression, identifying significant variables after multicollinearity tests. The urgency lies in the need for targeted regional policies for inclusive poverty alleviation, while the research's novelty lies in the application of the overdispersion model to the latest district/city data, complementing previous studies with a spatial focus on West Java. [Rusyana et al., 2021][Diz-Rosales et al., 2024]

Research Methods

This study uses a quantitative approach with the Generalized Linear Model (GLM) modeling method for count data, through Poisson regression and Negative Binomial regression on the number of poor people at the district/city level in West Java Province in 2024. The quantitative approach was chosen because the variables studied are measured in numerical form and analyzed using inferential statistical techniques, in line with the characteristics of quantitative research that is oriented towards testing the relationship between variables and generalizing findings. [Sugiyono, 2021] Before modeling, a multicollinearity test was carried out using Pearson correlation with the formula , as well as Variance Inflation Factor (VIF) with and Tolerance , where is the coefficient of determination of the regression of variables against other independent variables, to ensure there is no strong correlation between independent variables (VIF < 10 and Tolerance > 0.1). [Gujarati, 2004]$r_{xy} = \frac{\sum(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum(x_i-\bar{x})^2\sum(y_i-\bar{y})^2}} VIF_k = \frac{1}{1-R_k^2} TOL_k = 1 - R_k^2 R_k^2 X_k$

Table 1.Research Variables

Variables	Information	Unit
Y	Number of Poor People	Soul
x_1	Population density	Soul/km2
x_2	Percentage of Per Capita Expenditure on Food	%
x_3	Percentage of Open Unemployment Rate	%
x_4	Average Length of Schooling	Year
x_5	Labor Force Participation Rate	%
x_6	Gross Regional Domestic Product	Million rupiah
x_7	Number of Toddlers with Malnutrition	Soul
x_8	Percentage of Families with Access to Adequate Sanitation	%

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x_9	Number of Infant Mortality	Soul
$x10$	Percentage of Families with Access to Safe Drinking Water	%

The research instrument is a secondary data review sheet compiled to record the value of each variable from the official publication of the Central Statistics Agency (BPS) of West Java Province, including the number of poor people as the dependent variable and socio-economic indicators such as the open unemployment rate (), labor force participation rate (), GRDP (), proper sanitation (), and infant mortality () as independent variables. [Rusyana et al., 2021] The data were analyzed through descriptive statistics stages, multicollinearity tests, GLM modeling with Poisson distribution where the probability function and link function with , and Negative Binomial with and . [Santi & Rahayuningsih, 2023] The selection of the best model uses the Akaike Information Criterion (AIC) with the formula , where is the maximum likelihood and the number of parameters. [Akaike, 1987]$Y x_3 x_5 x_6 x_8 x_9 P(Y_i = y_i) = \frac{e^{-\mu_i}\mu_i^{y_i}}{y_i!} \log(\mu_i) = \eta_i = \beta_0 + \beta_1 x_{i1} + \cdots + \beta_k x_{ik} \mu_i = E(Y_i) = Var(Y_i) P(Y_i = y_i) = \frac{\Gamma(y_i+1/\alpha)}{\Gamma(1/\alpha) y_i!}\left(\frac{1}{1+\alpha\mu_i}\right)^{1/\alpha}\left(\frac{\alpha\mu_i}{1+\alpha\mu_i}\right)^{y_i} Var(Y_i) = \mu_i + \alpha\mu_i^2 AIC = -2\ln(\hat{L}) + 2k\hat{L}k$

The population in this study is all regencies and cities in West Java Province, with the unit of analysis being aggregate data at the district/city level in 2024, so that the study is a census of all available population elements. Thus, the research sample is the same as the population, namely 27 regencies/cities, so that no probabilistic or non-probabilistic sampling techniques are required, but data quality checks are still carried out to ensure completeness and consistency between observation units. [Sugiyono, 2021] This approach allows for interpretation of results that are directly relevant at the regional policy scale without the process of generalization to the wider population. [Creswell & Creswell, 2018]

The research procedure begins with the collection of secondary data from official BPS publications and related documents, followed by the preparation of a research data set containing response variables and predictors according to operational definitions. The next stage is data exploration through descriptive statistics, outlier checks, and initial assumption tests including multicollinearity tests. After the assumptions are met, GLM modeling is carried out with Poisson regression using maximum likelihood estimation (MLE) on the log-likelihood, checking for indications of overdispersion, and if overdispersion is found, it is continued with Negative Binomial regression modeling on the log-likelihood, followed by a comparison of AIC values to determine the best model and interpretation of parameter coefficients in the context of determinants of poverty in West Java. [Mann et al., 2014]$\ln L(\beta) = \sum[y_i \ln(\mu_i) - \mu_i - \ln(y_i!)] \ln L(\beta,\alpha) = \sum[\ln \Gamma(y_i + 1/\alpha) - \ln \Gamma(1/\alpha) - \ln(y_i!) + (1/\alpha)\ln(1/(1+\alpha\mu_i)) + y_i \ln(\alpha\mu_i/(1+\alpha\mu_i))]$

Results and Discussion

1. Descriptive Statistics

An overview of the poverty rate in West Java Province is presented in Table 2. This table shows the results of descriptive statistics that describe the research data, including the minimum, maximum, average (mean), and standard deviation values for each variable used. This descriptive statistical analysis aims to provide an initial understanding of the characteristics and distribution of data across districts/cities in West Java Province.

Table 2. Descriptive Statistics of Total Poverty Rate

Variables	N	Minimum	Maximum	Mean	Standard Deviation
x_1	27	1.03	15557.00	3608.88	4664.626
x_2	27	36.80	61.39	51.72	6,715
x_3	27	1.58	8.97	6.57	1,693
x_4	27	6.95	11.79	8.91	1,482

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x_5	27	62.58	80.12	68.06	3,442
x_6	27	24914.00	147081.00	53108.04	33264.175
x_7	27	407.00	9102.00	3521.96	2534.447
x_8	27	34.56	100.00	89.45	14,895
x_9	27	32.00	824.00	203.11	160,862
$x10$	27	85.37	99.85	95.10	4,221

Based on the results of the analysis,$x_1$has an average of 3,608.88 people per square kilometer with a standard deviation of 4,664.63, indicating an imbalance in population density between districts/cities.$x_2$has an average value of 51.72 and a standard deviation of 6.71, which indicates that the level of food consumption between regions is relatively uniform even though there are small differences.

Next, the variables$x_3$has a mean value of 6.57 and a standard deviation of 1.69, which means that the unemployment rate in West Java's regencies/cities is relatively stable without extreme variations.$x_4$of 8.91 years with a standard deviation of 1.48, indicating that the average population has completed education up to junior high school level.$x_5$has an average value of 68.06 and a standard deviation of 3.44, indicating fairly even workforce involvement across the region.

Variables$x_6$shows an average value of 53,108.04 with a high standard deviation of 33,264.17, reflecting the existence of economic inequality between districts/cities. The variable$x_7$has an average of 3,521.96 and a standard deviation of 2,534.45, indicating disparities in public health conditions between regions. The variable$x_8$has an average value of 89.45% with a standard deviation of 14.89, indicating that most households in West Java have access to adequate sanitation, although there are areas with below average conditions.

Furthermore,$x_9$has a mean value of 203.11 and a standard deviation of 160.86, which shows quite high variation between regions in basic health aspects. Finally, the variablex_{10}has an average of 95.10 with a standard deviation of 4.22, which shows that almost all districts/cities have good access to clean water.

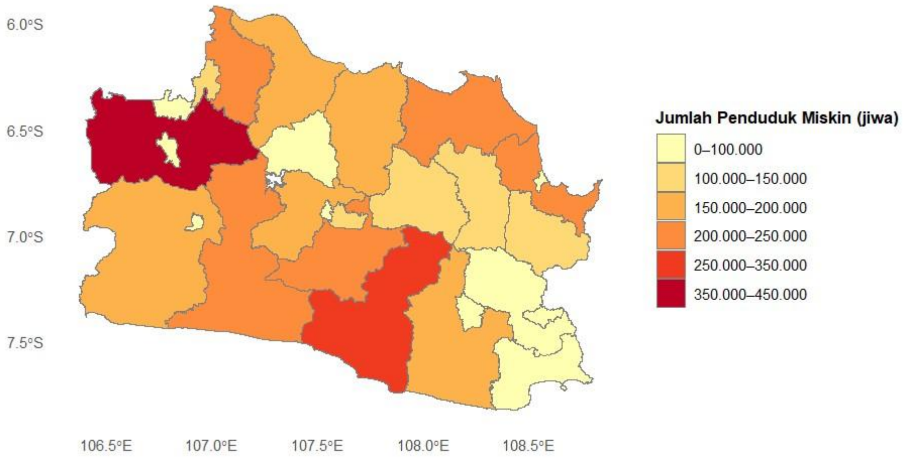

Figure 1. Mapping of the Number of Poor People in West Java Province in 2024

2. Correlation Analysis Between Variables

Correlation analysis between variables is performed to determine the extent of the linear relationship between the predictor variables in the model. This correlation test is important as a first step in detecting the possibility of multicollinearity, a condition where two or more independent variables are highly correlated with each other. Multicollinearity can cause regression model instability, increase the standard error of the coefficients, and reduce the validity of the estimation results.

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Table 3.Correlation Analysis Between Independent Variables

	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	$x10$
x_1	1,000	-0.845	0.008	0.854	-0.265	0.475	-0.194	-0.273	-0.085	0.482
x_2	-0.845	1,000	0.072	-0.904	0.522	-0.457	0.228	0.119	0.022	-0.605
x_3	0.008	0.072	1,000	0.059	-0.035	0.233	0.130	-0.174	0.083	-0.217
x_4	0.854	-0.904	0.059	1,000	-0.436	0.406	-0.317	-0.184	-0.110	0.546
x_5	-0.265	0.522	-0.035	-0.436	1,000	-0.354	-0.050	-0.014	-0.190	-0.574
x_6	0.475	-0.457	0.233	0.406	-0.354	1,000	-0.163	-0.180	0.092	0.319
x_7	-0.194	0.228	0.130	-0.317	-0.050	-0.163	1,000	0.167	0.767	-0.242
x_8	-0.273	0.119	-0.174	-0.184	-0.014	-0.180	0.167	1,000	0.063	0.079
x_9	-0.085	0.022	0.083	-0.110	-0.190	0.092	0.767	0.063	1,000	-0.181
$x10$	0.482	-0.605	-0.217	0.546	-0.574	0.319	-0.242	0.079	-0.181	1,000

Based on Table 3, it can be seen that several pairs of variables have very high correlation values, even exceeding the general tolerance limit of 0.5. Among these, there is a strong correlation between the variables$x_1$with$x_2$as big as-0.845, and between$x_1$with$x_4$of 0.854. In addition,x_2And$x_4$also has a very strong negative correlation, namely-0.904. This high correlation indicates that several variables have a close linear relationship, potentially causing multicollinearity problems in the regression model.

To address this issue, a process of eliminating variables with a correlation between predictors exceeding 0.5 was carried out. Based on the analysis results, the variables removed from the model were:x_1,x_2,x_4,x_7, Andx_{10}. The selection of deleted variables was based on the consideration that these variables have a strong correlation with several other predictors, thus potentially affecting the stability of the model as a whole.

Table 4. Latest Correlation Analysis Between Independent Variables

	x_3	x_4	x_5	x_6	x_8	x_9	x_{10}
x_3	1,000	0.059	-0.035	0.233	-0.174	0.083	-0.217
	x_3	x_4	x_5	x_6	x_8	x_9	$x10$
x_4	0.059	1,000	-0.436	0.406	-0.184	-0.110	0.546
x_5	-0.035	-0.436	1,000	-0.354	-0.014	-0.190	-0.574
x_6	0.233	0.406	-0.354	1,000	-0.180	0.092	0.319
x_8	-0.174	-0.184	-0.014	-0.180	1,000	0.063	0.079
x_9	0.083	-0.110	-0.190	0.092	0.063	1,000	-0.181
$x10$	-0.217	0.546	-0.574	0.319	0.079	-0.181	1,000

After the deletion, a new correlation table was obtained in Table 4 which only includes the variablesx_3 ,x_5,x_6,x_8, Andx_9. The correlation values between the variables in this table are all below 0.5, with a range between-0.35 to 0.23. This indicates that there is no longer a strong linear relationship between the predictors, so it can be concluded that there is no significant correlation between the variables after the variable elimination process.

3. Multicollinearity Test

A multicollinearity test is performed to ensure that there is no strong linear relationship between the predictor variables in the regression model. This test is performed by calculating the Variance Inflation Factor (VIF) and Tolerance values for each independent variable after standardizing the predictor data.

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A high VIF value indicates potential multicollinearity between the independent variables, while a low Tolerance value indicates a strong relationship between the variables.

Table 5. Multicollinearity Test

Variables	VIF	Tolerance
x3	1,224	0.817
x4	1,697	0.589
x5	1,849	0.541
x6	1,398	0.715
x8	1,130	0.885
x9	1,232	0.812
x10	2,326	0.430

Based on the calculation results in Table 5, all predictor variables have VIF values below the general tolerance limit of 5, with a range between 1.13 and 2.33. The tolerance values are also above 0.1, ranging from 0.43 to 0.89. This indicates that there are no serious symptoms of multicollinearity among the independent variables in the model. Therefore, all variables can be used simultaneously in the regression model because they meet the non-multicollinearity assumption.

4. Poisson Distribution Test

The results of the Poisson regression model parameter estimation using the GLM approach are presented in Table 6. This analysis was conducted to determine the influence of independent variables on the number of poor people (Y) in districts/cities in West Java Province. This model uses the log link function and the Poisson distribution, which are commonly used for data with count characteristics. Table 6 below shows the results of running the Poisson regression model.

Table 6.Results of Poisson Regression Parameter Estimation Using GLM

	Estimate	Std. Error	Z value	Pr(>|z|)
Intercept	4,810	0.184 *	261,110	$< 2e^{-16}$***
x_3	0.489 *	0.219 *	2,237	0.253 **
x_4	-0.401	0.247 *	-16,233	$< 2e^{-16}$***
x_5	-0.208 *	0.253 *	-0.821	0.411
x_6	0.342 *	0.214 *	1,600	0.110
x_8	-0.567 *	0.199 *	-2,851	0.044 ***
x_9	0.345	0.121 *	28,567	$< 2e^{-16}$***
$x10$	0.139 *	0.228 *	0.612	0.541

Significant. codes : 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

From these results it can be seen that the variable that has a significant influence on the poverty level is x_3, x_4, x_8, and x_9. The p-values of each are below 0.05, which means that the four variables have

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a significant relationship with the number of poor people. Meanwhile, the variable x_5, x_6, and x_{10} did not show a statistically significant effect.

Positive coefficient on variable x_3(0.489) and x_9(0.345) indicates that an increase in the open unemployment rate and infant mortality rate will increase the number of poor people. Conversely, the negative coefficient on the variable x_4(-0.401) and x_8(-0.567) shows that increasing the average length of schooling and access to proper sanitation will reduce the poverty rate in the region.

Based on the estimation results, the following Poisson regression equation is obtained:

$$\mu = e4.80982+0.04894x_3-0.40052x_4-0.02079x_5+0.03422x_6-0.05667x_8+0.34470x_9+0.01394x_{10}$$

The equation above shows that every one unit increase in the variable $x_3$and $x_9$will increase the expected value of the number of poor people, while an increase of one unit $x_4$and $x_8$will reduce the number of poor people exponentially.

Although the Poisson model can explain most of the data variation, an infinite AIC value indicates overdispersion. This indicates that the data variance is greater than the mean, making the Poisson model an inadequate fit. Therefore, the subsequent analysis used a Negative Binomial regression model, which can accommodate this overdispersion condition, to obtain more accurate results.

5. Negative Binomial Distribution Test

Further analysis was conducted using the Negative Binomial Regression model as an alternative to the Poisson model. This model was used because Poisson regression indicated overdispersion, which makes the Poisson model less than optimal in explaining data variation. Negative Binomial Regression has an additional dispersion parameter that can handle this difference, resulting in more stable and accurate estimation results. The estimated parameters of the Negative Binomial Regression are presented in Table 7 below:

Table 7. Negative Binomial Regression Parameter Estimation Results Using GLM

	Estimate	**Std. Error**	**Z value**	**Pr(>|z|)**
Intercept	4.7819052	0.852 *	56,134	$< 2e^{-16}$***
x_3	-0.999 ***	0.965 *	-0.010	0.992
x_4	-0.384	0.113	-3,381	7.22×10−4***
x_5	-0.283 *	0.118	-0.239	0.811
x_6	0.218 *	0.103	0.212	0.832
x_8	-0.834 *	0.926 *	-0.901	0.368
x_9	0.523	0.949 *	5,507	$3.65e^{-08}$***
$x10$	0.309 *	0.131	0.235	0.814

Significant. codes : 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

From these results it can be seen that the variable that has a significant influence on Y is $x_4$and x_9, with a p-value below 0.05. The other variable is x_3, x_5, x_6, x_8, and x_{10}has a p-value above 0.05 so it is not statistically significant.

Coefficient $x_4$negative value (-0.384), meaning that every one unit increase in $x_4$causes an exponential decrease in the number of poor people. On the other hand, the coefficient $x_9$has a positive value (0.523), indicating that a one unit increase in $x_9$has an effect on the increase in the number of poor people. Other variables do not significantly affect the model. Based on these estimation results, the following negative binomial regression equation is obtained:

$$\mu = e4.78191-0.00099x_3-0.38368x_4-0.02829x_5+0.02179x_6-0.08395x_8+0.52282x_9+0.03087x_{10}$$

The equation shows that the variable $x_4$plays a role in reducing poverty levels, while variable $x_9$plays a role in increasing it. Positive values at $x_9$strengthens the relationship between the increase in the

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variable and the increase in the number of poor people, while the negative value of $x_4$indicates the opposite effect.

6. Best Model

The best model was selected by comparing the AIC values between the Poisson regression model and the Negative Binomial regression model. The model with the lower AIC value was considered better because it indicated a better fit to the data with an efficient number of parameters.

Table 8. AIC

Poisson	Negative Binomial
∞	305.80007

Based on the comparison results in Table 8, it can be seen that the Poisson regression model has an infinite AIC value, while the Negative Binomial regression model has an AIC value of 305.8007. An infinite AIC value in the Poisson model indicates an overdispersion problem, where the data variance is much greater than its mean. This condition causes the Poisson model to be unable to provide efficient and accurate estimates of the data.

In contrast, the Negative Binomial model overcomes this problem by adding a dispersion parameter, resulting in more stable estimation results. Therefore, the Negative Binomial regression model was chosen as the best model to explain variations in poverty levels in West Java Province because it has a significantly lower AIC value than the Poisson model and is better able to handle inhomogeneous data distribution.

Conclusion and Recommendation

The results of the study indicate that the Negative Binomial Regression model is the best model for modeling the number of poor people in West Java Province with an AIC value of 305.8007, much better than the Poisson model which experiences overdispersion with an infinite AIC. Significant variables that influence the poverty rate are the average length of schooling (x_4) with a negative coefficient of -0.384 indicating that increasing education exponentially reduces poverty, and the number of infant deaths (x_9) with a positive coefficient of 0.523 indicating a strong relationship between basic health and poverty alleviation. These findings underscore the priority of investment in education and maternal and child health services as an effective strategy for reducing structural poverty at the district/city level.

This study has major limitations in the form of using cross-section data from 2024, which does not capture temporal dynamics and policy effects between periods. It also does not include structural variables such as infrastructure, migration, and local government program interventions. Furthermore, the aggregate district/city approach ignores intra-regional heterogeneity. For future research, it is recommended to use longitudinal panel data with spatial models such as Geographically Weighted Regression or the Spatial Durbin Model to capture inter-regional dependencies and long-term policy effects. Practically, the results of this study recommend prioritizing the allocation of the West Java regional budget to increase access to secondary education and reduce infant mortality through integrated community health centers (Puskesmas), which can form the basis for developing a more targeted 2025-2029 Regional Medium-Term Development Plan (RPJMD) to achieve SDG target number 1, the eradication of extreme poverty.

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