Generalized Poisson Regression Modeling Using Fisher-Scoring Optimization for Cases of Malnutrition in Toddlers in Central Java

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ABSTRAK

Gizi buruk pada balita berkontribusi terhadap 45% kematian anak global, sehingga diperlukan pemodelan risiko yang akurat. Di Jawa Tengah, data kasus gizi buruk menunjukkan overdispersi (ϕ = 162,58), yang menyebabkan model Poisson Regression (PR) tidak valid. Penelitian ini menerapkan Generalized Poisson Regression (GPR) dengan optimasi Fisher-Scoring pada lima variabel prediktor yakni imunisasi dasar lengkap, posyandu aktif, kunjungan neonatal, konsumsi tablet tambah darah (TTD) ibu hamil, dan penduduk miskin. Hasil evaluasi menunjukkan GPR lebih unggul dengan nilai AIC sebesar 505,68 dan Pearson Pseudo- R^2 sebesar 0,1784. Berdasarkan hasil pemodelan, konsumsi TTD dan jumlah penduduk miskin berpengaruh signifikan, sementara Posyandu aktif tidak signifikan. Lebih lanjut, variabel imunisasi dasar yang bertipe kategorik serta variabel kunjungan neonatal menunjukkan hasil anomali sehingga dieliminasi untuk menjaga stabilitas model. Penelitian ini membuktikan bahwa GPR memberikan estimasi yang lebih reliabel dalam mendukung kebijakan intervensi kesehatan dan pengentasan kemiskinan yang tepat sasaran di Jawa Tengah.

Kata kunci: Gizi Buruk; Generalized Poisson Regression; Fisher-Scoring

ABSTRACT

Malnutrition among infants and toddlers accounts for 45% of global child deaths, making accurate risk modeling essential. In Central Java, data on malnutrition cases show overdispersion (ϕ = 162.58), rendering the Poisson Regression (PR) model invalid. This study applied Generalized Poisson Regression (GPR) with Fisher-Scoring optimization to five predictor variables: complete basic immunization, active community health posts (posyandu), neonatal visits, iron-folic acid tablet (TTD) consumption by pregnant women, and living in poverty. The evaluation results show that GPR is superior with an AIC value of 505.68 and a Pearson Pseudo-R^2 of 0.1784. Based on the modeling results, iron tablet consumption and the number of poor residents have a significant effect, while active Posyandu does not. Furthermore, the categorical variable for basic immunization and the variable for neonatal visits showed anomalous results and were therefore eliminated to maintain model stability. This study demonstrates that GPR provides more reliable estimates to support targeted health intervention and poverty alleviation policies in Central Java.

Keywords: *Malnutrition; Generalized Poisson Regression; Fisher-Scoring*

INTRODUCTION

Malnutrition in toddlers contributes to approximately 45% of child deaths globally. In Central Java, the prevalence of 1% in 2022 requires appropriate and evidence-based interventions to identify complex risk factors [1]. Previous studies and national health profiles suggest that determinants such as basic immunization, active integrated health service posts (Posyandu), neonatal visit coverage, iron supplementation for pregnant women, and regional poverty levels play a significant role in maternal and child health outcomes [2][3][4][5].

Analyzing these determinants requires a robust statistical approach because malnutrition cases are categorized as count data, which is a discrete and non-negative value that requires a special model [6]. The general approach to analyzing count data is Poisson regression (PR), which relies on strict assumptions of equidispersion, where the mean equals the variance [7]. However, in public health data, this assumption is frequently violated by overdispersion, where the variance significantly exceeds the mean, leading to underestimated standard errors and misleading significance tests [8]. Therefore, a more flexible alternative is needed, such as Generalized Poisson Regression (GPR) [9]. GPR has the advantage of handling varying levels of dispersion by incorporating additional dispersion parameters while maintaining a structure that ensures model parameters remain consistent and easier to interpret [10].

Despite abundant malnutrition research, studies in Central Java specifically applying the GPR framework optimized by the Fisher-Scoring algorithm remain limited. This study addresses this gap by evaluating the aforementioned predictors, integrating categorical predictors (basic immunization) with numerical indicators. GPR is preferred over Negative Binomial Regression for its superior fit (lower AIC) in high-overdispersion scenarios [11]. Furthermore, the explicit use of Fisher-Scoring for MLE addresses the model's non-closed form by utilizing theExpected Information Matrix, offering better numerical stability and faster convergence. This technical precision is vital for producing valid estimators that accurately identify malnutrition determinants to support targeted health policies [12].

METHOD

Data and Variables

The study used secondary data taken from the 2024 Central Java Provincial Health Profile by the Central Java Provincial Health Office and the Central Statistics Agency (BPS). The data collected was the number of cases of malnutrition in children under five in each district/city in Central Java Province as the response variable. Meanwhile, several predictor variables used in this study are listed in Table 1.

Table 1. Predictor Variables

Variables	Description	Type	Definition
Y	Number of Cases of Malnutrition in Toddlers	Count	Total toddlers diagnosed with malnutrition.
X_1	Coverage of Infants Receiving Complete Basic Immunization	Nominal	1 if ≥ 80% (RPJMN target); 0 if < 80%.
X_2	Percentage of Active Posyandu	Ratio (%)	Percentage of active Posyandu in the region.

X_3	Percentage of Neonatal Care Visits	Ratio (%)	Percentage of complete neonatal visit coverage.
X_4	Percentage of Pregnant Women Who Take Iron Supplements	Ratio (%)	Percentage of pregnant women consuming ≥ 90 Iron (TTD) tablets.
X_5	Percentage of the Poverty Population	Ratio (%)	Percentage of population below the poverty line.

The selection of these predictor variables is based on the following theoretical basis from the [13]:

1. Immunization (X_1) acts as a primary preventive intervention to break the infection chain with an expected negative coefficient (-).
2. Active Posyandu (X_2) serves as the frontline for nutrition surveillance and early growth detection with an expected negative coefficient (-).
3. Neonatal Visits (X_3) are essential for detecting health disorders in newborns to prevent early growth faltering with an expected negative coefficient (-).
4. Iron Supplementation (X_4) is vital to prevent maternal anemia which determines the child's nutritional status with an expected negative coefficient (-).
5. Poverty (X_5) is a socio-economic determinant that restricts access to food and healthcare with an expected positive coefficient (+).

This study initially considers five predictor variables across 35 observations (districts/cities). This study used Rstudio as software to perform data analysis aimed at identifying factors that influence the number of malnutrition cases in Central Java Province.

Analysis Step

Procedurally, this study followed the following sequential steps.

1. Collecting data from 2024 Central Java Provincial Health Profile and the Central Statistics Agency (BPS) which were then combined into a single CSV dataset.
2. Analyzing the characteristics of the data for each research variable using descriptive statistics.
3. Testing for multicollinearity using the Variance Inflation Factor (VIF) to identify variables that are strongly related to each other. This test can be performed using formula (1).
$$VIF = \frac{1}{1-R_j^2} \tag{1}$$
Where R_j^2 is the coefficient of determination. If VIF > 10, this indicates multicollinearity among the predictor variables, which can be resolved by removing those variables.
4. Estimate the Poisson Regression (PR) model parameters using the MLE method and optimize them using the Fisher-Scoring algorithm.
5. Test whether there is overdispersion in the data by comparing the Pearson Chi-squared value with the degrees of freedom.
6. Estimate the Generalized Poisson Regression (GPR) model parameters using the MLE method and optimize them using the Fisher-Scoring algorithm.
7. Select the best model based on the smallest AIC and BIC, then evaluate the goodness of the best model using Pearson Pseudo-R^2.

Poisson Regression

Poisson Regression (PR) is a regression method commonly used to model response variables in the form of count data. This model assumes that the response variable follows a Poisson distribution. The probability function of the Poisson distribution is expressed in equation (2) below.

$$f(Y;\mu) = \frac{e^{-\mu}\mu^{y}}{y!};\ y_i = 0,1,2,\dots \tag{2}$$

The PR model itself is written as in equation (3).

$$\mu_i = \exp(\beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \dots + \beta_k x_{ki}) \tag{3}$$

Then, for estimating the Poisson Regression (PR) model parameters, the method used is Maximum Likelihood Estimation (MLE), which often does not provide explicit results, thus requiring the Fisher-Scoring numerical iteration method for optimization. The significance of the model parameters was evaluated simultaneously using the Maximum Likelihood Ratio Test (MLRT) and partially through the Wald z-test with a 5% significance level.

Overdispersion

Overdispersion is a condition in which the variance of the data is greater than its mean ($Var[Y] > E[Y]$). This violates a fundamental assumption of the Poisson regression (equidispersion). The test was conducted by calculating the dispersion ratio (ϕ) using the Pearson chi-square value as follows [14].

$$\phi = \frac{\chi^2}{df} \tag{4}$$

Where $\chi^2 = \sum_{i=1}^{n} \frac{(y_i - E(Y))^2}{N-p}$ and $df = n - p$, If the value $\phi > 1$ indicates overdispersion in the model [14]. Then, proceed to the Generalized Poisson Regression (GPR) model.

Generalized Poisson Regression

Generalized Poisson Regression (GPR) is an extension of conventional Poisson Regression (PR), designed as an alternative when the assumption of equidispersion is violated. The Generalized Poisson distribution uses an additional dispersion parameter that allows flexibility in modeling data variation. The probability function of the Generalized Poisson distribution can be expressed in the following equation (5).

$$f(Y;\mu,\theta) = \left(\frac{\mu_i}{1+\theta\mu_i}\right)^{y_i} \frac{(1+\theta\mu_i)^{(y_i-1)}}{y_i!} exp\left[-\frac{\mu_i(1+\theta y_i)}{1+\theta\mu_i}\right];\ y_i = 0,1,2,\dots \tag{5}$$

If the parameter $\theta = 0$, then this model will reduce to the classic Poisson distribution. The GPR model itself is the same as the Poisson Regression (PR) model, as shown in equation (6).

$$\mu_i = \exp(\beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \dots + \beta_k x_{ki}) \tag{6}$$

Next, to estimate the parameters, the Maximum Likelihood Estimation (MLE) method is used, which often does not provide explicit results, thus requiring the Fisher-Scoring numerical iteration method for optimization. The significance of the model parameters was evaluated simultaneously using the Maximum Likelihood Ratio Test (MLRT) and partially through the Wald z-test with a 5% significance level.

Fisher-Scoring

This algorithm is an optimization algorithm for estimating the Maximum Likelihood Estimation (MLE) method, which has a likelihood function that does not have a closed-form solution [15]. This algorithm was chosen because it has better numerical stability and faster convergence. In general, the Fisher-Scoring iteration step can be written in equation (7) as follows.

$$\beta^{(m+1)} = \beta^{(m)} + \left[I\left(\beta^{(m)}\right)\right]^{-1} g\left(\beta^{(m)}\right) \tag{7}$$

Where $g(\beta)$ represents the score vector and $I(\beta)$ is the Fisher information matrix. Iterations are performed until convergence criteria are met, namely when the change in parameter values between iterations is below a certain tolerance limit.

Model Evaluation

The best model can be determined by finding the smallest Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The formula for finding the AIC value can be written as in equation (8) below.

$$AIC = -2ln\, L\left(\tilde{\theta}\right) + 2k \tag{8}$$

Where $L\left(\tilde{\theta}\right)$ is the likelihood value and k is the number of parameters. Next, to find the BIC value, it can be calculated using the formula in equation (9) below.

$$BIC = -2ln\, L\left(\tilde{\theta}\right) + kln\,(n) \tag{9}$$

Where $L\left(\tilde{\theta}\right)$ is the likelihood value, k is the number of parameters, and n is the number of samples. Next, the best model selected will be evaluated using *Pseudo*-R^2 to determine how much the predictor variables contribute to explaining the response variable. The formula for calculating Pearson Pseudo-R^2 can be found using the formula in equation (10).

$$R_P^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \widehat{\mu_i})^2/\widehat{\mu_i}}{\sum_{i=1}^{n}(y_i - \bar{y})^2/\bar{y}} \tag{10}$$

The *Pseudo*-R^2 value ranges from 0 to 1. If the *Pseudo*-R^2 is in the range of 0.2 - 0.4, it indicates that the model fit is good, and if the *Pseudo*-R^2 is > 0.4, the model fit is very good [16].

RESULT AND DISCUSSION

Descriptive Statistics

Table 3 summarizes the characteristics of the research variables across 35 districts/cities in Central Java.

Table 3. Descriptive Statistics

Variables	Min	Max	Mean	Variance	Std. Deviation
Y	0	1091	383.6	88765.3	297.93
X_1	0	1	0.8571	0.1260	0.36
X_2	85.8	100	98.3571	11.7937	3.43
X_3	98	101.3	99.48	0.58	0.76
X_4	12.47	103.25	74.0671	738.0706	27.27
X_5	4.57	15.71	10.39	8.78	2.96

The data shows that the variance of Y (88,765.30) is greater than its mean (383.60). This indicates overdispersion in the data, justifying a switch to Generalized Poisson Regression (GPR). The distribution characteristics of the malnutrition cases in Central Java can be more clearly visualized in Figure 1 below.

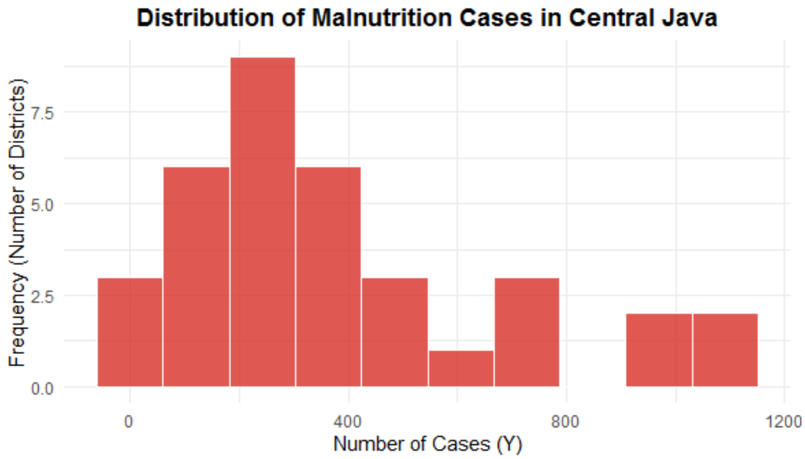

Figure 1. Distribution of Toddler Malnutrition Cases in Central Java

As illustrated in the Figure 1, the distribution of Y is highly right-skewed, characterized by a concentration of low-to-medium cases and several "outlier" districts reporting over 800 cases. Next, the preliminary relationships between variables are presented in the Figure 2

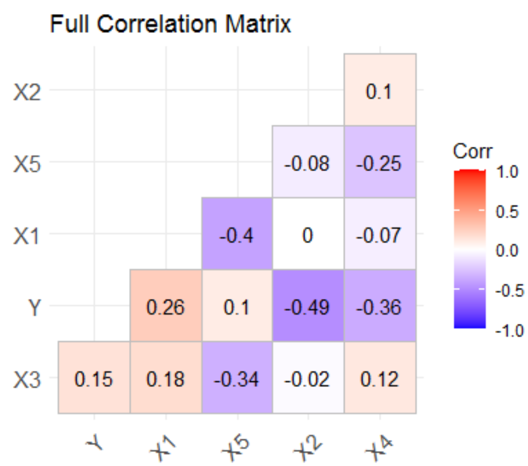

Figure 2. Correlation Matrix of Research Variables

Based on the correlation matrix in Figure 2, active Posyandu (X_2) and iron supplementation (X_4) exhibit negative correlations with the number of malnutrition cases, suggesting that higher coverage in these health services is associated with fewer cases. Conversely, the poverty population (X_5) shows a positive correlation, indicating that higher poverty levels tend to correspond with an increase in malnutrition. Meanwhile, the weak positive correlations observed for immunization (X_1) and neonatal visits (X_3) likely reflect a "detection bias," where regions with superior healthcare monitoring and reporting systems are more effective at identifying and recording existing cases compared to areas with less optimal surveillance. This statistical anomaly suggests that X_1 and X_3 may require further evaluation in the modeling stage to ensure the results remain consistent with theoretical expectations.

Multicollinearity Test

The multicollinearity diagnostic results for the three predictor variables are presented in Table 4 below.

Table 4. Variance Inflation Factor (VIF)

Variables	VIF	Tolerance
X_1	1.2381	0.8077
X_2	1.0161	0.9842
X_3	1.1356	0.8806
X_4	1.1147	0.8971
X_5	1.4130	0.7077

These results indicate that all variables have a VIF value below 5 and a Tolerance value significantly above 0.1. This confirms that there are no significant multicollinearity issues, so all predictor variables can be included simultaneously in the regression model without causing parameter estimation distortion.

Poisson Regression Model

The initial stage of modeling malnutrition cases in Central Java was conducted using standard Poisson regression with the Fisher-Scoring optimization method. The parameter estimation results for the Poisson regression model are presented in Table 5 below.

Table 5. Initial Estimation of Poisson Regression Model Parameters

Parameters	Estimate	Std. Error	z-value	p-value
β_0	-8.2725801	1.2356946	-6.695	**0.00000**
β_1	0.7178568	0.0357771	20.065	**0.00000**
β_2	-0.0904791	0.0023258	-38.902	**0.00000**
β_3	0.2266216	0.0122613	18.483	**0.00000**
β_4	-0.0071152	0.0003279	-21.700	**0.00000**
β_5	0.0451790	0.0034249	13.191	**0.00000**

Based on Table 5, although all variables showed a significant effect (p-value < 0.05), there was inconsistency between the estimation results and health theory (theoretical expectations). Variables X_1 (Immunization) and X_3 (Neonatal Visits) showed positive coefficients. This phenomenon confirms the presence of detection bias that was identified during the descriptive analysis stage. Therefore, to maintain model stability and the accuracy of interpretation, the model was re-estimated by eliminating the variables with illogical relationships. The estimation results for the simplified Poisson model (3 variables) are presented in Table 6.

Table 6. Refined Estimation of Poisson Regression Model Parameters

Parameters	Estimate	Std. Error	z-value	p-value
β_0	15.6444647	0.2270855	68.892	**0.00000**
β_2	-0.0918689	0.0022889	-40.136	**0.00000**
β_4	-0.0086223	0.0003136	-27.496	**0.00000**
β_5	-0.0028441	0.0029152	-0.976	0.329

Based in Table 6, variables X_2 and X_4 remain significant with a direction of association consistent with theory (negative), while X_5 becomes insignificant under the standard Poisson framework. However, the extremely high z-values in both tables above are a strong indication of overdispersion, which causes the Standard Error to be underestimated. This underscores the need for a formal overdispersion test before moving to the Generalized Poisson Regression (GPR) model.

Overdispersion Test

To validate the Poisson model, an overdispersion test was performed by calculating the dispersion ratio ϕ. The diagnostic results show a Pearson Chi-Square of 5040.01 with 31 degrees of freedom, yielding a dispersion ratio of 162.58. Since the ratio is greater than 1, it confirms the presence of overdispersion. Consequently, the standard Poisson model is unsuitable, necessitating the use of Generalized Poisson Regression (GPR) to obtain more reliable estimates.

Generalized Poisson Regression Model

Modeling was continued using Generalized Poisson Regression (GPR) due to overdispersion, which was also optimized with Fisher-Scoring to obtain parameter estimation results. The modeling results are presented in Table 7 below.

Table 7. Estimation of Generalized Poisson Regression Model Parameters

Parameters	Estimate	Std. Error	z-value	p-value
β_0	9.244316	3.816657	2.422	**0.0154**
β_2	-0.064615	0.038423	-1.682	0.0926
β_4	-0.009845	0.003992	-2.466	**0.0136**
β_5	0.069511	0.035223	1.973	**0.0484**

Based on Table 7, at a 5% significance level, the variables TTD Consumption (X_4) and Poor Population (X_5) were found to have a significant effect on cases of malnutrition. Meanwhile, the variable Active Posyandu (X_2) was not significant at the 5% level but was retained to maintain model stability. The estimation results were obtained with 23 iterations of Fisher-Scoring until a convergent value was obtained.

Selecting and Evaluating the Best Model

Next, the best model was selected based on the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values, where models with smaller AIC and BIC values indicated better performance. The results of the evaluation of the two models are presented in Table 8.

Table 8. AIC & BIC Model

Model	AIC	BIC
Poisson Regression	5716.718	5722.939
Generalized Poisson Regression	**505.6782**	**513.4549**

As shown in Table 8, the GPR model yields significantly lower AIC and BIC values compared to the PR model. The substantial drop in AIC from 5716.718 to 505.6782 is a direct result of the GPR model's ability to account for the overdispersion (ϕ = 162.58) in the dataset. Consequently, GPR is selected as the superior model. The resulting GPR model is stated as follows (11).

$$\mu_i = \exp(9.244316 - 0.064615X_2 - 0.009845X_4 + 0.069511\, X_5) \quad (11)$$

Based on the GPR estimation results, only X_4 and X_5 have a significant effect (p-value < 0.05). Interpretively, the coefficient X_4 of -0.009845 confirms that a 1% increase in iron supplementation coverage for pregnant women reduces the number of malnutrition cases by $\exp(-0.009845) = 0.990203$. The coefficient X_5 of 0.069511 confirms that a 1% increase in poverty population increase the number of cases by $\exp(0.069511) = 1.07198$.

The significant impact of Iron Supplementation (X_4) and Poverty Population (X_5) in the GPR model underscores the critical interplay between maternal health, economic conditions, and child nutrition. The effectiveness of iron supplements reflects a vital link between maternal well-being and nutritional outcomes, a finding that aligns with the research by [4] and [5]. Conversely, the insignificance of Active Posyandu (X_2) in this study, which differs from the results reported by [2], reveals an important methodological truth. While primary health services are essential, their direct statistical association with the specific volume of malnutrition cases in Central Java weakens once extreme overdispersion is correctly addressed. Interestingly, the insignificance of Basic Immunization (X_1) in the GPR model, which differs from the research by [2], reveals an important methodological truth. Although immunization is vital for overall child survival, its direct correlation with the volume of malnutrition cases in Central Java is not as strong as nutrition interventions and primary care when overdispersion is correctly accounted for. This suggests that to reduce malnutrition rates, the government must go beyond general health targets and focus specifically on strengthening nutrition programs and maternal support.

Furthermore, evaluation using Pearson Pseudo-R^2 produces a value of 0.1784. This means that the response variable explain approximately 17.84% of the variation in malnutrition cases, while the rest is influenced by other models that are not included in the model.

CONCLUSION

This study concludes that Generalized Poisson Regression (GPR) is the superior model for analyzing toddler malnutrition in Central Java, effectively addressing extreme overdispersion (ϕ = 162.58) by reducing the AIC to 505.68 with a Pearson Pseudo-R^2 of 0.1784. Methodologically, the transition from a standard Poisson model was essential to avoid underestimated standard errors and misleading significance, especially since predictor variables with categorical types provided no significant effect in this framework. Practically, the GPR results reveal that Iron Supplementation (X_4) and Poverty Population (X_5) are the primary significant drivers of malnutrition cases, while the influence of Active Posyandu (X_2) weakened in this robust model. Consequently, health policies should prioritize targeted maternal nutritional support and poverty alleviation to effectively suppress regional malnutrition rates.

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