Modelling infant mortality rate in Central Java, Indonesia use generalized poisson regression method

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Abstract. The infant mortality rate is the number of deaths under one year of age occurring among the live births in a given geographical area during a given year, per 1,000 live births occurring among the population of the given geographical area during the same year. This problem needs to be addressed because it is an important element of a country's economic development. High infant mortality rate will disrupt the stability of a country as it relates to the sustainability of the population in the country. One of regression model that can be used to analyze the relationship between dependent variable Y in the form of discrete data and independent variable X is Poisson regression model. Recently The regression modeling used for data with dependent variable is discrete, among others, poisson regression, negative binomial regression and generalized poisson regression. In this research, generalized poisson regression modeling gives better AIC value than poisson regression. The most significant variable is the Number of health facilities (X1), while the variable that gives the most influence to infant mortality rate is the average breastfeeding (X9).

Keywords: Infant Mortality Rate, Poisson Regression, Generalized Poisson Regression.

1. Introduction
Mortality is one of three demographic components other than fertility and migration that can affect the age and population composition. The World Health Organization (WHO) defines death as an event of permanent disappearance of all signs of life, which can occur at any time after the birth of life. One commonly used mortality indicator is infant mortality (IMR). Countries with high per capita income generally have low infant mortality rates [1-2].

According to Indonesia Demographic and Health Survey 2012, three main causes of infant mortality are acute respiratory infections, fever, and diarrhea. The combined causes of these causes 32 percent of infant deaths. In line with the Millennium Development Goals (MDGs) achievement targets, the Ministry of Health has set a target of reducing IMR in Indonesia from an average of 36 deaths per 1000 live births to 23 per 1000 live births by 2015.

Based on research shows that individual, household and arround environment variables had a significant impact on mortality rate. At the Enviroment variable, particularly in regions where the odds of neonatal death is significantly higher, the availability of skilled birth attendants and quality of the health infrastructure have significant impact in reducing neonatal mortality. At the household and individual levels, appropriate postnatal care service utilization and the benefits of birth spacing and health promotion strategies to increase awareness of the importance of timely are needed given
their protective effect on mortality rate. Interventions to prevent low birth weight would also contribute to further reductions of neonatal mortality in Indonesia. Public health interventions directed at reducing neonatal death should address environmental, household and individual level factors which significantly influence mortality rate in Indonesia [3]. According [4], use of an unskilled birth attendant (45% of births) and giving birth at home are most common among the poorest and least educated women. The children of these women have the highest risk infant mortality.

According to the Convention on the Rights of the Child [5], newborns have a right to enjoy the highest attainable standard of health. Although, the research show that the child mortality has revealed that the proportion of under-five child deaths occurring in the first month of life has been increasing [6]. Despite accounting for almost 40 per cent of all under-five child deaths and more than half of infant deaths, the infant mortality rate is not a target of the Millennium Development Goals (MDGs) [7]. However if the MDG target of a two-thirds reduction in child mortality by 2015 is to be achieved then infant mortality rate must be decreased.

Several other studies have been conducted, research in South Sulawesi says that the death rate due to lack of health facilities. The spread of health personnel in Indonesia is uneven, especially remote areas. [8]. Frankenburg’s (1995) [9] study for Indonesia revealed that adding maternity clinics and doctors to villages reduce the risks of infant mortality.

Regression analysis is a method used to analyze the relationship between dependent variable (Y) and independent variable (X). In general, regression analysis is used to analyze data with dependent variable in the form of continuous random variable [10]. Not all dependent variables in the regression analysis are continuous, there are also discrete dependent variables. The regression analysis used to model the dependent variable is discrete is Poisson regression. Poisson, binomial negative and generalized poisson regression models have been used to model data with discrete dependent variables [36-38]. These are type of regression based on Poisson distribution. However, applications of these models are based on certain assumptions. For instance, standard Poisson regression model assumes equal mean and variance of the dependent variable. In reality, often this equality assumption is not true because the variance could be higher than mean (over-dispersion property) or lower than mean (under-dispersion property). Ignorance of these properties may produce biased standard errors and inefficient estimates of regression parameters, even the estimates of the standard Poisson model are still consistent. The negative binomial regression model is more flexible than the Poisson model and is frequently used to analyse outcome variable with over-dispersion. The GPR model, on the other hand, can capture both over- and under-dispersion properties of the data, which make this model even more flexible [37].

However, a count variable like number of infant mortality rate often shows under-dispersion property. Our data also shows the under-dispersion property. Therefore we applied the GPR model to model of infant mortality rate. The first objective was to demonstrate the applicability of this model as an alternative to study the child malnutrition in infant mortality rate in Indonesia. The second objective was to find some predictors of the count variable defined as the number of under-nine infant mortality rate in Indonesia.

2. Literature Review

2.1 Generalized Poisson Regression

Poisson Regression is the application of Generalized Linear Model (GLM) which describes the relationship between response variable Y discrete data distributed poisson with variable predictor X. If Y is a discrete data with a distributed Poisson with the parameter \( \mu > 0 \) then the function of the probability mass is

\[
    f(y; \mu) = \frac{e^{-\mu} \mu^y}{y!}; \quad y = 0, 1, 2, \ldots
\]

Assumed \( E(y) = \mu \) and \( Var(y) = \mu \)

In Eq. (1) can be written as:
In Eq. (2) is a form of equation of the exponential family distribution function with 
\( b(\theta_i) = \exp(\theta_i), a(\phi) = 1 \), and \( c(y_i, \phi) = -\log(y_i!) \) with \( \theta_i = \log(\mu_i) \). Variance and mean as follow:

\[ E(Y_i) = b'(\theta_i) = \exp(\theta_i) = \mu_i \quad \text{and} \quad \text{Var}(Y_i) = b''(\theta_i) = \exp(\theta_i) = \mu_i. \]

When \( g(\mu_i) \) is the same as the natural parameter \( \theta \), where \( g \) is a log function, the canonical link (a function that transforms the mean value to the natural parameter) is log link: \( g(\mu_i) = \log(\mu_i) \) using the link function obtained by poisson regression model in the form:

\[ \ln \mu = X\beta \quad \text{when} \quad \mu_i = \exp(X_i\beta) \quad \text{and} \quad \mu_i = \exp(\beta_0 + \beta_1 x_{i1} + \cdots + \beta_p x_{ip}) \]

\( \mu_i \) is expectation value and \( Y_i \) Poisson distributed.

The method used to estimate the parameters in the Poisson regression is the Maximum Likelihood Estimation (MLE) method. MLE can be performed if the distribution of the data is known. The first step is to determine the likelihood function of the Poisson regression model. Assuming \( Y_1, Y_2, \ldots, Y_n \) are a set of randomly independent variables and \( y_i \sim \text{Poisson}(\mu_i) \) then the likelihood function for the Poisson regression model is

\[ L(y_i; \beta) = \prod_{i=1}^{n} f(y_i; \beta) = \prod_{i=1}^{n} \frac{\mu_{i}^{y_i} \exp(-\mu_i)}{y_i!} \]

Furthermore from likelihood function is taken logarithm value so that obtained function log likelihood from equation (3) as follows:

\[ \log L(y_i; \beta) = \log \left( \prod_{i=1}^{n} f(y_i; \beta) \right) \]

To test the significance of Poisson regression parameters can be used Maximum Likelihood Ratio Test method (MLRT) with test procedure as follows:

Hypotesis

\[ H_0 : \beta_1 = \beta_2 = \cdots = \beta_j = 0 \]
\[ H_1 : \text{At least one of} \quad \beta_j \neq 0, j = 1, 2, \ldots, p \]

According to Greene (2000) the test statistic used in this method is as follows:

\[ G = 2 \left[ \ln \left( \frac{L(\hat{\omega})}{L(\hat{\Omega})} \right) \right] \]

\( (L(\hat{\omega})) \) is log without likelihood variable (set of parameters under \( H_0 \)). \( \omega = \{\beta_0| -\infty < \beta_j < \infty\} \).

\( (L(\hat{\Omega})) \) is a log of likelihood with variables (the set of parameters under the population).

\[ \Omega = \{\beta_0, \beta_1, \beta_2, \ldots, \beta_p| -\infty < \beta_j < \infty, j = 0, 1, 2, \ldots, p\} \]

Criteria of test, reject \( H_0 \) if \( G_{\text{hitung}} \geq \chi^2_{v, \alpha} \) with \( v \) is the number of parameter model under the population minus the number of parameters under \( H_0 \).

Furthermore, the significance test of each regression coefficient is done. This test is performed primarily in cases where the predictor variables are more than one, the goal is to select the predictor variables that affect the response variable. The test procedure is as follows:

Hypotesis:

\[ H_0 : \beta_i = 0 \quad \text{(not significant)} \]
\[ H_0 : \beta_i \neq 0 \quad \text{(significant)} \]

Test of statistics

\[ t_i = \frac{\hat{\beta_i}}{SE(\hat{\beta_i})} \]

Criteria test reject \( H_0 \) if \( |t_i| > t_{v, \alpha} \), where \( \alpha \) is level of significant and \( v \) is degree of freedom.
2.2 Overdispersion
The Poisson regression assumes the count data has the same variance value as its mean (equidispersion), but in reality the counting data often shows the dispersion, whether overdispersion or underdispersion. Overdispersion is one of the most common problems in Poisson regression. The count data in the Poisson regression is said to be it if the variance value is greater than the mean. It has the same impact as violations of homocedasticity assumptions in linear regression models [12]. The problem of it does not appear in classical linear regression, whose response variables are normally distributed, since the distribution has its own parameters (variance) that show variability. To detect the occurrence of overdispersion problems in the Poisson regression model, it can be done by testing the relationship between variant and mean in the form of equation

\[ \text{Var}(Y) = \phi \mu \]  

(4)

Where constant \( \phi \) is the parameter of the dispersion / scale parameter. Equation (4) shows the overdispersion state of the Poisson regression model if the value \( \phi \) is greater than one. In its application, the overdispersion of Poisson regression can be seen from the Pearson chi-square statistical value divided by degrees of freedom or can also divide the value of devianis with degrees of freedom, if the result approaches 1 means no overdispersion occurs in the Poisson regression model.

2.3 Generalized Poisson Distribution
The generalized Poisson distribution was first introduced by Consul and Jain in 1973, then discussed more widely by Jain in 1989. The density function of the Poisson distribution is generalized to the parameters \( \theta \) and \( \lambda \) as follows:

\[
f(y; \theta, \lambda) = \theta(y + \lambda)^{y-1} \frac{1}{y!} \exp(-\theta - y\lambda) \text{ with } y = 0, 1, 2, \ldots
\]

The mean and variance values of the generalized Poisson distribution are as follows.

Mean \( E(Y|\theta, \lambda) = \mu = \frac{\theta}{1-\lambda} \) and variance \( \text{Var}(Y|\theta, \lambda) = \frac{\theta}{(1-\lambda)^2} \).

2.4 Generalized Poisson Regression
In generalized poisson regression model, \( y_i \) is dependent variable and \( x_{i1}, x_{i2}, \ldots, x_{ip} \) are independent variable.

\[
f(y; \theta, \lambda) = \theta(\theta + \lambda y)^{y-1} \frac{e^{-(\theta + \lambda y)}}{y!}; \quad y = 0, 1, 2, \ldots
\]

(5)

with \( \mu = \frac{\theta}{1-\lambda} = \theta \phi \) and \( \phi \) is dispersion parameter where \( \phi = \frac{1}{1-\lambda} \). Then the density function of Generalized Poisson Regression as follow as:

\[
f(y; \mu, \phi) = \mu[\mu + (\phi - 1)y]^{y-1} \frac{\phi^y}{y!} \exp\left[\frac{\mu + (\phi - 1)y}{\phi}\right]
\]

(6)

If \( \phi = 1 \) then the generalized poisson regression model would be poisson regression model, and if \( \phi > 1 \), then generalized poisson regression model will be presented count data with overdispersion.

Generalized Poisson Regression model can be written as:

\[
y_i = X\beta + \epsilon
\]

\[
y_i = E(Y_i|x_i)
\]

\[
y_i = \mu
\]

\[
E(Y_i|x_i) = \mu_i = x_i^T \beta
\]

The value of \( x_i^T \beta \) can be resulted negative value, so that it needs transformation value can be written:
\[ \eta_i = \log(\mu_i) = x_i^T \beta \]

Likelihood function of Generalized Poisson Regression model can be written as:

\[ L(y_i; \phi, \beta) = \prod_{i=1}^{n} \mu_i^{y_i} \exp\left(\frac{-\mu_i + \phi y_i}{\phi - 1}\right) \frac{\phi^y}{y!} \]

The estimation parameter of this model is:

\[ \hat{\phi} = \frac{1}{(n-p)} \sum_{i=1}^{n} \frac{(Y_i - \hat{\mu}_i)^2}{\hat{\mu}_i} = \chi^2 \]

With

\[ \chi^2 = \sum_{i=1}^{n} \frac{(Y_i - \hat{\mu}_i)^2}{\text{var}(\hat{Y}_i)} = \sum_{i=1}^{n} \frac{(Y_i - \hat{\mu}_i)^2}{\nu(\hat{\mu}_i)} = \sum_{i=1}^{n} \frac{(Y_i - \hat{\mu}_i)^2}{\phi \hat{\mu}_i} \]

So that the estimation can be written as

\[ \hat{\phi} = \frac{1}{(n-p)} \left[ 2 \sum_{i=1}^{n} Y_i \log\left(\frac{Y_i}{\hat{\mu}_i}\right) - (Y_i - \hat{\mu}_i) \right] \]

To test the generalized poisson regression parameters used the test statistic of devian value. The generalized Poisson regression regression testing procedure is:

Hypothesis
- \( H_0 : \beta_1 = \beta_2 = \cdots = \beta_p = 0 \)
- \( H_1 : \) at least one of \( \beta_j \neq 0, j = 1,2, \ldots, p \)

The test statistic used in this method is as follows;

\[ G = -2 \left[ \ln \frac{L(\hat{\omega})}{L(\hat{\Omega})} \right] \]

\( (L(\hat{\omega})) \) is log likelihood without variable (set of parameter under \( H_0 \)) with \( \omega = \{ \beta_0 | -\infty < \beta_j < \infty \} \).

\( (L(\hat{\Omega})) \) a is log likelihood with variable (set of parameter under population) with \( \Omega = \{ \beta_0, \beta_1, \beta_2, \ldots, \beta_p | -\infty < \beta_j < \infty, j = 0,1,2, \ldots, p \} \)

Criteria of test, reject \( H_0 \) if \( G_{\text{hiung}} \geq \chi^2_{v,\alpha} \) with \( v \) is the number of parameter.

Furthermore, the significance test of each regression coefficient is done. The test procedure is as follows:

Hypotesis
- \( H_0 : \beta_i = 0 \) (not significant)
- \( H_0 : \beta_i \neq 0 \) (significant)

Test of statistics:

\[ t_i = \frac{\hat{\beta}_i}{SE(\hat{\beta}_i)} \]

Criteria of test, reject \( H_0 \) if \( |t_i| > t_{\alpha/2, v} \)

3. Results and Disscusions
The following descriptive statistics are presented for research data on factors affecting infant mortality. The number of predictor variables used by 9 units from each district / city in Central Java taken in 2015. Predicting variables include the number of health facilities (Hospital or other public health) in each district / city (\( X_1 \)); number of medical personnel (doctors and midwives) in each district / city (\( X_2 \)); percentage of childbirth with non-medical assistance (TBAs) in each district / city (\( X_3 \)); percentage of Slum Households in each district / city (\( X_4 \)); population density each km\(^2\) in each district / city (\( X_5 \)); percentage of clean and healthy living behaviors of each district / city (\( X_6 \)); percentage of population who do not have health insurance each district / city (\( X_7 \)); percentage of children less than 2 years of age exclusively breastfed each district / city (\( X_8 \)); average breastfeeding per district / city (\( X_9 \)).
Table 1. Descriptive Statistics of Factors Infant Mortality Rate in Central Java in 2015

| Variable | Mean  | SE    | StDev | Variance | Minimum | Q1    | Median | Q3    | Maximum |
|----------|-------|-------|-------|----------|---------|-------|--------|-------|---------|
| Y        | 159.2 | 12.6  | 74.8  | 5595.3   | 25      | 126   | 152    | 201   | 384     |
| X⁰       | 31.11 | 1.85  | 10.96 | 120.1    | 10      | 26    | 30     | 38    | 55      |
| X¹       | 224.1 | 30    | 177.4 | 31472.3  | 78      | 133   | 185    | 247   | 1024    |
| X²       | 0.905 | 0.205 | 1.215 | 1.476    | 0       | 0     | 0      | 1.6   | 5.33    |
| X³       | 2.38  | 0.239 | 1.412 | 1.995    | 0.83    | 1.31  | 2.16   | 2.89  | 7.65    |
| X⁴       | 2236  | 450   | 2660  | 7075315  | 475     | 843   | 1109   | 1852  | 11633   |
| X⁵       | 78.77 | 1.72  | 10.2  | 104.11   | 55.89   | 73.93 | 83.93  | 110.98| 146.33  |
| X⁶       | 48.33 | 2.28  | 13.48 | 181.68   | 5.69    | 41.66 | 49.29  | 57.92 | 69.66   |
| X⁷       | 50.27 | 2.42  | 14.3  | 204.45   | 21.48   | 38.31 | 53.28  | 60.72 | 76.07   |
| X⁸       | 10.782| 0.253 | 1.495 | 2.234    | 6.18    | 9.74  | 10.59  | 11.85 | 14.25   |

Based on Table 1, the average number of health facilities in the form of hospitals amounted to 30s, at least only 10 whereas the most reached 55. The average number of medical personnel both doctors and nurses reached 211 people. The percentage of birth attendant in the form of saman on average reaches only 0.905%. The average percentage of slum households only reached 2.38%. The average of population per km² reaches 2236 people. The average percentage of RTs who apply a clean and healthy lifestyle reaches 78.77%. The average of percentage of people who do not have health insurance reach 48.33%. The average percentage of children less than 2 years of age exclusively breastfed reaches 50.27%. The average length of breastfeeding reaches 10 months. The first step taken in modeling poisson regression is to test the distribution of the response variable whether it is poisson distributed or not. Testing of Poisson Distribution on Response Variables as follow as:

The Poisson distribution test on the response variable is done by Kolmogorov-Smirnov Test with the following test procedure:

Hypotesis:
H₀: The response variable data follows the Poisson distribution
H₁: The response variable data not follows the Poisson distribution

Significant level 5%, obtained p-value = 0.066 > α = 0.05. Since the value of p-value> α, then H₀ is accepted. The response variable data follows the Poisson distribution

3.1. Modelling Poisson Regression for Infant Mortality Rate in Central Java, Indonesia.

Below is the estimation result of poisson regression model of infant mortality rate in Central Java.

Table 2. Estimation of parameters Poisson Regression for Infant Mortality Rate in Central Java 2015

| Parameter | Estimation | Standard Error | Degree of freedom | t-value | P-Value |
|-----------|------------|----------------|-------------------|---------|---------|
| β₀        | 3.6243     | 0.1863         | 35                | 19.45   | <0.0001 |
| β¹        | 0.02428    | 0.001712       | 35                | 14.18   | <0.0001 |
| β²        | -0.00017   | 0.000114       | 35                | -1.51   | 0.1401  |
| β³        | 0.06621    | 0.01419        | 35                | 4.67    | <0.0001 |
| β⁴        | -0.05885   | 0.01553        | 35                | -3.79   | 0.0006  |
| β⁵        | -4.86E-06  | 0.00001        | 35                | -0.48   | 0.6359  |
| β⁶        | -0.00924   | 0.001745       | 35                | -5.29   | <0.0001 |
| β⁷        | 0.00686    | 0.001299       | 35                | 5.28    | <0.0001 |
| β⁸        | 0.00167    | 0.001148       | 35                | 1.45    | 0.1548  |
| β⁹        | 0.09746    | 0.01165        | 35                | 8.36    | <0.0001 |
Table 2 shows the results of the estimated Poisson regression model for infant mortality rate in Central Java in 2015. According to the table, the significant variables are the number of health facilities (Hospital or other public health) \((X_1)\), percentage of childbirth with non-medical assistance in each district / city \((X_3)\), percentage of Slum Households \((X_4)\), percentage of clean and healthy living behaviors \((X_6)\), percentage of population who do not have health insurance \((X_7)\) and average breastfeeding \((X_9)\). The greatest significance value is variable the number of health facilities \((X_1)\), while the variable that gives the biggest contribution in determining infant mortality rate in Central Java is average breastfeeding \((X_9)\). Furthermore, to see the effect of predictor variables significantly affecting the response variable, it is modeled again by involving only significant predictor variables. Table 3 is an estimate of the best Poisson regression model for infant mortality in Central Java.

**Table 3. Estimation of parameter Poisson Regression for the Best Model Infant Mortality Rate in Central Java 2015**

| Parameter | Estimasi | Standard Error | Degree of Freedom | t     | P-Value |
|-----------|----------|----------------|-------------------|-------|---------|
| \(\beta_0\) | 3.7875   | 0.1719         | 35                | 22.04 | < 0.0001|
| \(\beta_1\) | 0.02369  | 0.001436       | 35                | 16.49 | < 0.0001|
| \(\beta_2\) | 0.07107  | 0.01298        | 35                | 5.48  | < 0.0001|
| \(\beta_3\) | -0.07062 | 0.01285        | 35                | -5.5  | < 0.0001|
| \(\beta_4\) | -0.01008 | 0.001419       | 35                | -7.1  | < 0.0001|
| \(\beta_5\) | 0.007959 | 0.00121        | 35                | 6.58  | < 0.0001|
| \(\beta_6\) | 0.09072  | 0.01085        | 35                | 8.36  | < 0.0001|

Based on Table 3, it shows that the most significant variable is \(X_1\), while the biggest influence is \(X_9\). So the best Poisson regression model is as follows:

\[
\ln(\hat{\mu}) = 3.7875 + 0.02369X_1 + 0.07107X_3 - 0.07062X_6 - 0.01008X_7 + 0.007959X_9 + 0.09072X_9
\]

The value of AIC model 696.7 is lower than the AIC value when all the variables are inserted, i.e. 699.9, meaning that the Poisson regression model with the smallest AIC is the best poisson model. The next step is multicollinearity. It is using Variance in Factor (VIF). If a VIF value greater than 5 indicates a multicollinearity occurs between the predictor variables. Here’s the VIF value for each predictor.

**Table 4. Multicollinearity checking for All Predictors**

| Variables | VIF’s value | Decision |
|-----------|-------------|----------|
| \(X_1\)  | 1.354       | Non multicollinearity |
| \(X_3\)  | 1.319       | Non multicollinearity |
| \(X_4\)  | 1.170       | Non multicollinearity |
| \(X_6\)  | 1.242       | Non multicollinearity |
| \(X_7\)  | 1.154       | Non multicollinearity |
| \(X_9\)  | 1.202       | Non multicollinearity |

Table 4 shows that there is no multicollinearity among the predictor variables, so that all significant predictor variables can be used for modeling infant mortality in central Java.
3.2. Overdispersion analysis to Infant Mortality Rate in Central Java

The analysis of overdispersion cases was used to find out whether the poisson regression model obtained fulfilled the assumption, by looking at the deviance value of poisson regression model of infant mortality rate in Central Java.

Table 5. Deviance Value for Poisson Regression Model Data on Infant Mortality Rate in Central Java Province in 2015

| Criteria             | Value     | DF | Value/DF |
|----------------------|-----------|----|----------|
| Deviance             | 445.5328  | 28 | 15.9119  |
| Pearson Chi Square   | 464.6788  | 28 | 16.5957  |

Table 5 shows the deviance value of the Poisson regression model is 445.5328. If the value of deviance is divided by degrees of freedom it will produce a dispersion value of 15.9119 which value is greater than 1. This indicates the overdispersion of the poisson regression model of infant mortality in Central Java. Therefore, to overcome this, used Generalized Poisson Regression modeling.

3.3. Modelling Generalized Poisson Regression for Infant Mortality Rate in Central Java, Indonesia.

The following is given the result of parameter estimation of Poisson regression model.

Table 6. Estimation of parameters Generalized Poisson Regression Model Infant Mortality Rate in Central Java.

| Parameter | Estimation | Standard Error | DF | t-value | p-value |
|-----------|------------|----------------|----|---------|---------|
| $\beta_0$ | 3.7229     | 0.6775         | 35 | 5.5     | <.0001  |
| $\beta_1$ | 0.03155    | 0.006182       | 35 | 5.1     | <.0001  |
| $\beta_2$ | 0.07287    | 0.04808        | 35 | 1.52    | 0.1386  |
| $\beta_3$ | -0.04161   | 0.035          | 35 | -1.19   | 0.2424  |
| $\beta_4$ | -0.0129    | 0.006115       | 35 | -2.11   | 0.0421  |
| $\beta_5$ | 0.007453   | 0.003898       | 35 | 1.91    | 0.0641  |
| $\beta_6$ | 0.09053    | 0.03802        | 35 | 2.38    | 0.0228  |
| $\omega$  | 0.01719    | 0.003012       | 35 | 5.71    | <.0001  |

Based on Table 6 the significant variables are Number of health facilities ($X_1$), percentage of clean and healthy living behaviors ($X_6$); average breastfeeding ($X_9$). The value of $\omega > 0$ indicates that the generalized poisson regression represents overdispersed data. The next step is to re-model the significant variables. Here is the result of estimating the parameters of the best generalized poisson regression model:

Table 7. Estimation parameters of Generalized Poisson Regression For the Best Model

| Parameter | Estimation | Standard Error | DF | t-value | p-value |
|-----------|------------|----------------|----|---------|---------|
| $\beta_0$ | 4.1968     | 0.7359         | 35 | 5.7     | < 0.0001|
| $\beta_1$ | 0.03601    | 0.006891       | 35 | 5.23    | < 0.0001|
| $\beta_2$ | -0.01709   | 0.006725       | 35 | -2.54   | 0.0156  |
| $\beta_3$ | 0.09656    | 0.04199        | 35 | 2.3     | 0.0275  |
| $\omega$  | 0.02014    | 0.003355       | 35 | 6       | < 0.0001|
Based on the table, the variable that has a high level of significance is Number of health facilities ($X_1$), while for the variable that gives the biggest effect on infant mortality rate in Central Java is average breastfeeding ($X_9$). The generalized Poisson regression model obtained is as follows:

$$\hat{\mu} = \exp(4.1968 + 0.03601X_1 - 0.01709X_6 - 0.090656X_9)$$

4. Conclusion
In this research, generalized poisson regression modeling gives better AIC value than poisson regression. The most significant variable is the Number of health facilities ($X_1$), while the variable that gives the most influence to infant mortality rate is the average breastfeeding ($X_9$). Generalized poisson regression modeling produces less significant predictor variables than poisson regression. This research can be continued by studying the relationship of region factor to infant mortality rate in Central Java.

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