Generalized Poisson Regression Modeling on the Number of Infant Deaths in East Nusa Tenggara Province in 2022

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ABSTRAK

Jumlah kematian bayi di Provinsi Nusa Tenggara Timur (NTT) masih berada di atas rata-rata jumlah kematian bayi secara nasional. Penelitian ini dilakukan untuk menentukan model *Generalized Poisson Regression* (GPR) dalam mengatasi overdispersi pada model regresi poisson pada kasus jumlah kematian bayi serta untuk melihat faktor-faktor yang berpengaruh signifikan terhadap jumlah kematian bayi di Provinsi NTT. Variabel penelitian yang digunakan yakni jumlah kematian bayi sebagai variabel repson, dan sejumlah variabel prediktor yang diduga dapat mempengaruhi variabel respon. Data yang digunakan merupakan data sekunder yang diperoleh dari publikasi Badan Pusat Statistik (BPS) Provinsi Nusa Tenggara Timur (NTT) dari setiap 22 Kota/Kabupaten. Hasil penelitian menunjukkan bahwa data jumlah kasus kematian bayi mengalami overdispersi dengan rasio antara deviance dan derajat kebebasan sebesar 3,578. Pemodelan dengan GPR menunjukan bahwa model dengan 5 variabel bebas menghasilkan model yang optimal dengan nilai AIC sebesar 184,145. Kelima variabel yang berpengaruh signifikan terhadap jumlah kematian bayi di Provinsi NTT yakni persentase rumah tangga dengan akses sanitasi layak, persentase persalinan ditolong oleh pihak diluar tenaga medis, jumlah remaja yang mendapat penyuluhan kesehatan reproduksi, persentase penduduk usia 0-59 bulan menurut pemberian imunisasi tidak lengkap, dan jumlah fasilitas kesehatan.

Kata kunci: Jumlah Kematian Bayi, Generalized Poisson Regression (GPR), Overdispersi

ABSTRACT

The number of infant deaths in East Nusa Tenggara (NTT) Province is still above the national average. This research was conducted to investigate the Generalized Poisson Regression (GPR) model for addressing the overdispersion in the Poisson regression model of the number of cases of infant deaths and to explore the potential factors influencing the number of infant deaths in the province. The variable used is the number infant mortality as a response variable, and the number of predictor variables that are thought to influence the response variable. The data used is secondary data obtained from the publication by the Central Statistics Agency of ENT Province from each of the 22 cities/regencies. The study shows data on the number of cases of infant mortality experienced overdispersion with a ratio between deviance and degrees of freedom of 3.578. Modeling with GPR shows that the model with 5 independent variables produces an optimal model with an AIC value of 184.145. Those variables are the percentage of households with access to adequate sanitation, the percentage of births assisted by parties other than medical personnel, the number of teenagers who received reproductive health counseling, the percentage of the population aged 0-59 months who received incomplete immunization, and the number of health facilities.

Keywords: *Number Of Infant Deaths; Generalized Poisson Regression (GPR), Overdispersion*

INTRODUCTION

The number of babies who die before the age of one year in a certain period is known as the Infant Mortality Rate (IMR). Infant mortality remains a major problem throughout the world, especially for developing countries, even though IMR worldwide has made progress in reducing infant mortality [1].

Based on the results of the Indonesian Demographic and Health Survey (IDHS), there was a decrease in IMR in 2022 compared to the previous year, where infant mortality in 2022 was 16.85/1,000 Live Births while in 2017 it was 24/1,000 Live Births. Based on data on infant mortality in Indonesia, there has been a decrease in IMR, but it is still quite high when compared to other ASEAN countries, which is 4.2 times higher than Malaysia and 1.2 times higher than the Philippines [2].

Based on the results of the 2020 Population Census Long Form, it explains that IMR in East Nusa Tenggara Province (NTT) is 25.67/1,000 live births. The high IMR in NTT Province is caused by many factors including factors directly related to infants, one of which is related to low birth weight (LBW) which is the leading cause of infant mortality. The distribution of infant mortality cases in NTT Province is spread across all regions, however, the distribution pattern and mapping of the distribution of death cases have not been optimally investigated.

Data shows that the number of infant deaths in NTT Province continues to increase. In 2022, There are about 1244 cases, of which 114 cases were in Kupang district which is the highest infant mortality of 22 district in the province. Therefore, due to the characteristics of the district that vary from one another, it is necessary to investigate the potential factor contributing to this infant death this by developing a mathematical model. The distribution of infant mortality cases in NTT Province is spread across all regions, however, the distribution pattern and mapping of the distribution of death cases have not been optimally investigated [3].

The number of infant deaths is one example of count data where the data distribution follows the Poisson distribution [4]. In modeling with the Poisson regression model, the assumption of equal dispersion should be satisfied namely the mean and variance of the response variable must be the same. However, this condition is often violated when using real data where the mean of response variable is lower than variance, or vice versa so that the use of the Poisson regression model is no longer effective. For this, other methods are needed, for example using the Generalized Poisson Regression (GPR) model. The use of the GPR model is very effective in overcoming the problem of overdispersion [5–8]. For this reason, the GPR model will be applied to investigate the factors that influence the number of infant deaths in NTT Province. The results of this study are expected to contribute to the local government in designing health policy to reduce the IMR in NTT Province.

METHOD

Data Source

The data sources used in this study are secondary data regarding cases of infant mortality and factors suspected of influencing it in NTT Province in 2022. Data were obtained from the publication of the Central Statistics Agency (BPS) of NTT Province in figures 2023 and People's Welfare Statistics [9]. The unit analysis of this study is 22 cities/regencies in NTT Province.

Research Variables

The research variables consist of response variables (Y) and predictor variables (X). The response variables used in this study are the number of infant deaths (Y), as well as predictor variables which are factors suspected to influence the number of infant deaths in 22 districts/cities in NTT Province. The following are details of the predictor variables of this study.

X_1 = Percentage of poor population
X_2 = Percentage of households with access to proper sanitation
X_3 = Percentage of deliveries assisted by parties other than medical personnel
X_4 = Percentage of deliveries assisted by midwives/nurses
X_5 = Percentage of pregnant women under 19 years old
X_6 = Number of adolescents who received reproductive health education
X_7 = Percentage of population aged 0-59 months according to incomplete immunization
X_8 = Percentage of population aged 0-23 who have ever been breastfed
X_9 = Number of health facilities
X_{10} = Number of health workers

Analysis Methods and Analysis Steps

Data analysis was supported by SPSS software. The data processing steps are as follows: firstly, we conducted a descriptive statistic to find out the general picture of data on infant mortality and its predictors in NTT Province in 2022. Then we applied Poisson distribution test to assess the distribution of data.

The Poisson distribution test is used to determine whether the response variable in this study is distributed Poisson or not. For this reason, the Kolmogorov-Smirnov test will be used in this Poisson distribution test. The hypotheses used are as follows:

H_0 = The number of infant deaths is distributed Poisson
H_1 = The number of infant deaths is not distributed Poisson

The test statistics used are,

$$D_{count} = \max |F_n(x) - F_0(x)| \quad (1)$$

Then, we conducted a multicollinearity test**.** In the Poisson regression model, there are several assumptions that must be met. One of them is that there is no multicollinearity between predictor variables. Multicollinearity is a situation that indicates a strong correlation or relationship between two or more predictor variables in a model. Detection of multicollinearity cases can be done by looking at the Variance Inflation Factor (VIF) value. If the VIF value is greater than 10, then there is multicollinearity between the predictor variables [10]. The test statistics in multicollinearity are,

$$VIF = \frac{1}{(1 - r_{i,j}^2)} \quad (2)$$

Where $r_{i,j}$ is the correlation coefficient X_i and Y_j.

Furthermore, we conducted a Poisson regression modeling. The Poisson regression is a non-linear regression model that is often used to model the relationship between response variables in the form of discrete data (counts) with predictor variables in the form of discrete or continuous data [11]. The following is the general form of the Poisson regression equation for ten predictors.

$$\mu_i = \exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \cdots + \beta_{10} X_{10}) \qquad (3)$$

In evaluating the effect of each parameter to the model in equation 3, we conducted a test for testing the significance of model parameters. Firstly, we did a simultaneous test. This test used the results of the omnibus test. The omnibus test is a likelihood ratio test to determine whether all predictor variables collectively improve the model compared to the intercept model alone. In this test, all predictor variables are tested together to see whether the predictor variables jointly affect the response variable [12]. In the omnibus test, there are the results of the likelihood ratio chi-square which is usually symbolized as G^2. The following are the criteria for the hypothesis being tested

$H_0: \beta_0 = \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7 = \beta_8 = \beta_9 = \beta_{10} = 0$

$H_1: at\ least\ there\ is\ \ \beta_k \neq 0, k = 1,2,3, \dots, 10$

Test Statistics used,

$$G^2 = 2\sum_{i=1}^{n}(y_i x_i^T \hat{\beta} - \exp(x_i^T \hat{\beta}) - (y_i \hat{\beta}_0 \exp(\hat{\beta}_0))) \qquad (4)$$

The omnibus test is expected to have a value of $G^2 > \chi^2_{table}$ that can reject the null hypothesis, or can be explained in the following table. Secondly, we conducted the partial test aimed to determine the predictor variables having a significant effect on the response variable [13]. The Wald test will be used to obtain predictor variables that have a significant effect on the response variable. The following are the test hypothesis criteria used

$H_0: \beta_k = 0, for\ k = 1,2, \dots, 10$

$H_1: \beta_k \neq 0, for\ k = 1,2,3, \dots, 10$

The test statistics in the partial test are,

$$W = \frac{(\hat{\beta}_k)}{SE\ (\hat{\beta}_k)} \qquad (5)$$

Where $\hat{\beta}_k$ is the estimated value for parameter $\hat{\beta}_k$ and $SE\ (\hat{\beta}_k)$ is the estimated standard error of $\hat{\beta}_k$. The decision to be taken is if the $p - value < \alpha$ with the significance level used is 5% or the value of the Wald test is greater than X^2_{table}.

On the next stage, we did a test to investigate the possibility of the overdispersion of the data. When using Poisson regression, the equidispersion assumption must be met, namely the assumption of equality between the mean and variance values. However, Poisson regression modeling sometimes contains overdispersion, namely when the variance value is greater than the mean value. The phenomenon of overdispersion can be written as $var\ (Y) > E(Y)$. Conversely, data whose variance is smaller than the mean is called underdispersion. The phenomenon of underdispersion can be written as $var\ (Y) < E(Y)$. Overdispersion can be indicated by the deviance and Pearson chi-squares values divided by the degrees of freedom [14]. If both values are more than 1, then overdispersion is said to occur. Finally, we conducted modeling of Generalized Poisson Regression (GPR) and interpreting the results.

RESULT AND DISCUSSION

Descriptive Statistics.

Descriptive statistics aims to determine the characteristics of each variable. Variables are described using the amount of data, minimum value, maximum value, average value, standard deviation and variance in Table 1. To see the number of infant mortality cases in each city/district in NTT, it can be seen in the following Figure 1.

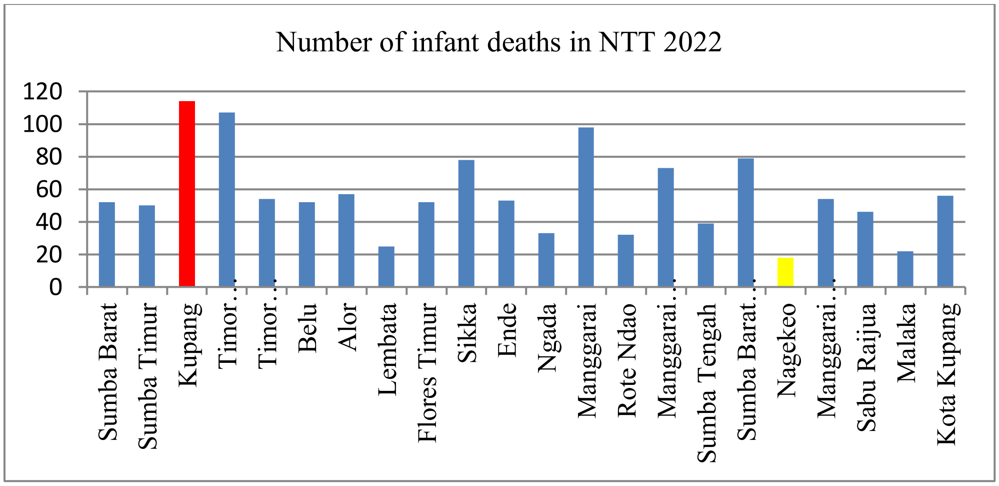

Figure 1. Graph of Infant Mortality Rate in East Nusa Tenggara Province in 2022

From Figure 1, the lowest number of infant mortality cases was 18 cases in Nagekeo Regency. Meanwhile, the highest number of infant mortality cases was 114 cases in Kupang Regency in 2022.

Table 1. Characteristics of Infant Mortality Data in NTT Province in 2022

Variables	N	Min	Max	Mean	Std. Deviation	Variance
Y	22	18	114	56,5455	25,98668	675,307
X_1	22	8,61	32,51	20,7732	6,91628	47,835
X_2	22	45,83	88,82	73,7091	14,17349	200,888
X_3	22	0	29,22	9,26	8,21708	67,520
X_4	22	658	8065	6389,2273	1650,08865	2722792,565
X_5	22	12	2764	1373,6091	822,31369	676199,8
X_6	22	200	1200	596,5909	239,20696	57219,968
X_7	22	22,20	49,19	33,4759	7,99320	63,891
X_8	22	83,75	100	95,6568	4,42380	19,570
X_9	22	224	927	520,7727	187,83628	35282,0170
X_{10}	22	126	1985	1108,4091	493,9801	244016,348

From Table 1, the average number of infant deaths in NTT Province in 2022 was 56.5455 or 56 cases with a variance of 675.307.

Poisson Distribution.

Following the equation (1), the Kolmogorov-Smirnov test had been applied to test Poisson distribution of the dependent variable. The value of Kolmogorov-Smirnov test is presented in Table 2.

Table 2. *Kolmogorov-Smirnov* Test Result

$One - Sample\ Kolmogorov - Smirnov$		
		Y
N		22
$Most\ Extreme\ Differences$	$absolute$	0,264
$Asymp. Sig. (2 - tailed)$		0,093

From Table 2, obtained the Kolmogorov-Smirnov test value for $D_{count} = 0{,}264$ which is in the absolute value. While the $D_{table} = 0{,}281$ for a significance level of 5%. The $D_{count}(0{,}264) < D_{table}(0{,}281)$ is obtained or can be seen from the $p - value\ (0{,}093) > \alpha\ (0{,}05\ )$ then accept H_0 which means the number of infant mortality cases in NTT Province in 2022 is following the Poisson distribution.

Multicollinearity Test.

The strong correlation or relationship between two or more predictor variables was evaluated by looking at the Variance Inflation Factor (VIF) as indicated in equation (2). The results of the multicollinearity test on the number of infant mortality cases in NTT Province in 2022 are shown in the Table 3 below.

Table 3. VIF Values on Predictor Variables

Variables	VIF
Poor population (X_1)	2,843
Households with access to proper sanitation (X_2)	1,972
Delivery assisted by parties other than medical personnel (X_3)	3,140
Delivery assisted by midwives/nurses (X_4)	2,857
Pregnant women <19 years old (X_5)	1,816
Adolescents who receive reproductive health counseling (X_6)	2,029
Age 0−59 months who are given incomplete immunization (X_7)	2,444
Age 0-23 months who are given breast milk (X_8)	1,846
Health facilities (X_9)	2,549
Health workers (X_{10})	2,924

From Table 3, it can be seen that the VIF value of each predictor variable is less than 10, so there is no multicollinearity between the predictor variables of the number of infant mortality cases in NTT Province.

Poisson Regression Modeling.

In developing Poisson regression model, firstly, we did a simultaneous test by determining the value of the omnibus test as indicated in equation (4). The omnibus test is a likelihood ratio test to determine whether all predictor variables collectively improve the model compared to the intercept model alone. The value of Omnibus Test was presented in Table 4 below.

Table 4. Simultaneous Parameter Testing Using Omnibus Test

Omnibus Test	
Likelihood Ratio Chi-Square	206,149
df	10
Sig	0,000

Based on Table 4, if the model value (sig) $> \alpha$ or the $G^2 > \chi^2_{table}$, it means that H_0 is accepted. Because the model value (sig) in the omnibus test is 0,00 $> \alpha$ (0,05) or the $G^2(206{,}149) > \chi^2_{tabel}(18{,}307)$, then H_0 is rejected. So, it can be concluded that there is one or more predictor variables that have a significant relationship to the number of infant mortality cases in NTT Province in 2022.

Secondly, we conducted the partial test by calculating the Wald test value as shown in equation (5). The estimation of each parameter model and the value of Wald test for each predictor variable was presented in Table 5.

Tabel 5. Parameter Estimation Value

Parameter Estimation				
Parameter	Estimation	SE	Sig	*Wald Chi-Square*
β_0	3,286	0,9548	0,001	11,844
β_1	-0,003	0,0074	0,716	0,133
β_2	-0,013	0,0031	0,000	16,338
β_3	0,019	0,0065	0,003	8,729
β_4	-1,837e-5	3,2925e-5	0,577	0,311
β_5	-6,500e-6	4,2133e-5	0,877	0,024
β_6	0,001	0,0002	0,000	18,702
β_7	-0,019	0,0059	0,002	9,809
β_8	0,012	0,0092	0,185	1,757
β_9	0,001	0,0002	0,000	18,144
β_{10}	8,311e-5	9,6760e-5	0,390	0,738

Based on Table 5, the values (sig) of the parameters $\beta_0 = 0{,}001, \beta_2 = 0{,}000, \beta_3 = 0{,}003, \beta_6 = 0{,}000, \beta_7 = 0{,}002,$ dan $\beta_9 = 0{,}000$ are obtained, where the value of each parameter is smaller than the significance level used, which is 0,05. As well as the Wald Chi-Square test value, from each parameter $\beta_0 = 11{,}844;\ \beta_2 = 16{,}338;\ \beta_3 = 8{,}729;\ \beta_6 = 18{,}702;\ \beta_7 = 9{,}809;$ dan $\beta_9 = 18{,}144$ where this value is greater than $X^2_{table} = 3{,}8415$. Then H_0 is accepted, which means that the predictor variables, namely the percentage of households with access to proper sanitation, the percentage of deliveries assisted by parties other than medical personnel, the number of adolescents who receive reproductive health education, the percentage of the population aged 0-59 months according to incomplete immunization, and the number of health facilities have a significant effect on the number of infant deaths in NTT province in 2022. Therefore the initial model of the number of infant mortality cases in NTT Province is

$$\mu_i = \exp(3{,}431 - 0{,}015X_2 + 0{,}024X_3 + 0{,}001X_6 - 0{,}019X_7 + 0{,}001X_9) \quad (6)$$

Testing the overdispersion of the data

Overdispersion can be indicated by the deviance and Pearson chi-squares values divided by the degrees of freedom [14,15]. If both values are more than 1, then overdispersion is said to occur. The results of the overdispersion test are presented in the Table 6 below.

Table 6. Overdispersion Test Results

Infant and toddler mortality	*Value*	*df*	*Value/df*
Deviance	39,359	11	3,578
Pearson cji-square	39,166	11	3,561

Table 6 shows that the Deviance value and Pearson Chi Square value are 3,578 and 3,561 respectively, which are more than 1. This shows that the Poisson regression model does not meet the equidispersion assumption or experiences overdispersion so that the Poisson regression model is not suitable for modeling the number of infant mortality cases in NTT Province in 2022. Therefore, further analysis was carried out using the Generalized Poisson Regression (GPR) model.

Generalized Poisson Regression (GPR) Modeling on the Number of Infant Mortality Cases in East Nusa Tenggara Province in 2022.

To determine the GPR model, namely by estimating and testing parameters where previously a simultaneous test had been carried out to see which variables had a significant effect on the model, but only involving one or several predictor variables selected based on the smallest Akaike Information Criteria (AIC) value [16,17]. AIC is a statistical measuring tool used to measure model suitability. The following are the results of the AIC test.

Tabel 7. AIC Values of All Selected Models

Variables	AIC Value	Model
X_2, X_3, X_6, X_7, X_9	184,145	$\exp(4{,}283 - 0{,}013X_2 + 0{,}019X_3 + 0{,}001X_6 - 0{,}019X_7 + 0{,}001X_9)$
X_2, X_3, X_6, X_9	196,242	$\exp(3{,}592 - 0{,}012X_2 + 0{,}011X_3 + 0{,}001X_6 + 0{,}001X_9)$
X_2, X_6, X_9	201,794	$\exp(3{,}862 - 0{,}015X_2 + 0{,}001X_6 + 0{,}001X_9)$
X_3, X_9	240,849	$\exp(2{,}985 + 0{,}017X_3 + 0{,}002X_9)$
X_9	260,159	$\exp(3{,}136 + 0{,}002X_9)$

Based on Table 7, the best model selected based on the smallest AIC value is the model involving $X_2, X_3, X_6, X_7,$ dan X_9 as predictor variables that have a significant effect with an AIC value of 184.145. So, the Generalized Poisson Regression model for infant mortality cases in NTT Province in 2022 is

$$\mu = \exp(4{,}283 - 0{,}013X_2 + 0{,}019X_3 + 0{,}001X_6 - 0{,}019X_7 + 0{,}001X_9) \quad (7)$$

Based on the model above, it can be interpreted as follows, if the variable has a constant value, then the number of infant deaths in NTT Province in 2022 that occurred was an average of $e^{4{,}283}$ or 74,457 cases. Each additional 1 coefficient of household population with Access to Proper Sanitation will reduce the average number of infant deaths by $e^{-0{,}013}$ or 0,987 cases. The more households that have inadequate access to proper sanitation, the more the number of infant deaths in each district/city will increase by 1 case.

Each additional 1 coefficient of childbirth assisted by parties other than medical personnel will increase the average number of infant deaths by $e^{0{,}019}$ or 1,019 cases. This means that if each delivery assisted by parties other than medical personnel increases, the number of infant deaths in each district/city will also increase by 1 case.

Each additional 1 coefficient of adolescents who receive reproductive health counseling will increase the average number of infant deaths by $e^{0{,}001}$ or 1,001 cases. This means that every teenager who receives reproductive health counseling is likely to increase the number of infant deaths in each district/city by 1 case.

Every additional 1 coefficient of the population aged 0-59 months according to incomplete immunization will reduce the average number of infant deaths by $e^{-0{,}019}$ or 0,981 cases. This means that the population at that age according to incomplete immunization can reduce the number of infant deaths in each district/city by 1 case.

Every additional 1 coefficient of health facilities will cause an increase in the average number of infant deaths by $e^{0{,}001}$ or around 1,001 cases. This means that if the health facilities obtained by the community increase, it is likely to increase the number of infant deaths in each district/city by 1 case.

CONCLUSION

The distribution of infant death is uneven in NTT Province with the highest was in Kupang district. The GPR model for representing the cases in this province in 2022 is $\mu = \exp(4{,}283 - 0{,}013X_2 + 0{,}019X_3 + 0{,}001X_6 - 0{,}019X_7 + 0{,}001X_9)$. Of the ten factors suspected of influencing the response variable, there are five factors that have an impact on the number of toddler deaths in NTT Province in 2022, which is the percentage of households with access to proper sanitation (X_2), the percentage of deliveries assisted by parties other than medical personnel (X_3), the number of adolescents receiving reproductive health education (X_6), the percentage of the population aged 0-59 months according to incomplete immunization (X_7), and the number of health facilities (X_9).

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