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MODELING THE NUMBER OF INFANT AND MATERNAL MORTALITY CASES USING BIVARIATE GENERALIZED POISSON REGRESSION IN WEST JAVA PROVINCE

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Abstract:

The Maternal Mortality Rate (MMR) and Infant Mortality Rate (IMR) cannot be separated because the health condition of pregnant women has a direct impact on fetal development and health. This is in accordance with the 2025-2029 National Medium-Term Development Plan (RPJMN) and the 2030 Sustainable Development Goals (SDGs), in which West Java Province aims to reduce the Maternal Mortality Rate (MMR) and Infant Mortality Rate by 4 to 5%. This study aims to estimate the number of maternal and infant deaths and examine the factors involved using the Bivariate Generalized Poisson Regression (BGPR) approach. This Method chosen because it can overcome overdispersion problem in independent data has correlated in Maternal mortality Rate (MMR) and Infant Mortality Rate (IMR) in West Java Province 2024. Parameter estimation is performed using the Maximum Likelihood Estimation (MLE) method and hypothesis testing using the Maximum Likelihood Ratio Test (MLRT) method. Selecting the best model using the smallest AIC value and the result of the study obtained using p-value 0.05 show that percentage of iron supplementation (Fe90), Percentage of Childbirth Assisted by Health Workers, Percentage of visits by pregnant women (K4), Percentage of obstetric complications treated have a significant effect on maternal mortality rates, while Percentage of childbirth Assisted by Health workers and Percentage of visits by pregnant women (K4) had a significant effect on infant mortality rates.

1. Introduction

The Maternal Mortality Rate (MMR) is one indicator of women's health, determined by the number of deaths caused by pregnancy, childbirth, and the postpartum period. Maternal deaths in this indicator are defined as all deaths during pregnancy, childbirth, and the postpartum period, but not due to accidents or incidents. The level of Maternal Mortality Rate (MMR) is a measure of a country's capability. According to (Rahmadini et al., 2023) This is also reinforced by the Sustainable Development Goals (SDGs), which are sustainable development goals agreed upon by the United Nations (UN) on October 21, 2015, with the goal of a world free from death, environmental damage, and fear. One of the indicators of the 17 SDGs focuses on health issues, and this is included in goal number three is good

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health and well-being. There are 38 targets to be achieved in the health sector according to the SDGs, including efforts to reduce the Maternal Mortality Rate (MMR) and Infant Mortality Rate (IMR) (Miftahussurur et al., 2023).

In Indonesia, the Maternal Mortality Rate (MMR) and Infant Mortality Rate (IMR) are still a challenge that must be faced, especially in West Java province, which has the largest population in Indonesia. According to data from the West Java Provincial Health Office, in 2024 there was a decrease in cases compared to the previous year, where the number of reported maternal deaths decreased by 43 cases from 792 deaths in 2023. This was due to appropriate measures taken by launching various maternal and child health service programs (Dewi et al., 2025). Data from health office in west java in 2024 show that the districts with maternal mortality cases are Bogor district 105 cases; Garut district 50 cases, and Bekasi 46 cases, while infant mortality cases in West Java Province increased compared to 2023, with 5,533 cases. There has been a fluctuating trend in these figures compared to the previous year, as well as a pattern that can be seen from the number of cases over the last five years (Dewi et al., 2025).

Research on factors affecting maternal mortality has been conducted extensively, including by (Aminullah & Purhadi, 2020) which modelled maternal and infant mortality cases in East Java using univariate and bivariate Poisson regression approaches with the assumption of equidispersion (equality between the mean and variance). Further development of the method was carried out by (Rahmadini et al., 2023) which analyzed similar factors in Central Java in 2021 using Generalized Bivariate Poisson Regression (BGPR), an approach that can overcome the limitations of equidispersion assumptions. A latest study by (Setiawan & Purhadi, 2025)reapplied the BGPR method to model maternal and infant mortality in lampung, demonstrating the consistency and relevance of this approach in public health analysis.

Generalized Bivariate Poisson Regression (BGPR) can be used not only on bivariate count data with positive, zero, or negative correlations, but also on bivariate count data that is under/overdispersion (Purwanti et al., 2021). According to (Purwanti et al., 2021) Data with excessive dispersion will result in overdispersion or variance greater than the mean value. This violates the assumption of equidispersion in Poisson regression modelling, which will produce invalid conclusions. Therefore, cases of under dispersion or overdispersion must be handled using a generalized Poisson regression approach. This study will analyze two dependent variables, the Maternal Mortality Rate (MMR) and Infant Mortality Rate (IMR) in West Java Province in 2024 and obtain the best model using the Bivariate Generalized Poisson Regression (BGPR) approach for maternal and infant mortality data in West Java Province in 2024.

2. Literature Review

2.1 Bivariate Generalized Poisson Regression

Bivariate Generalized Poisson Regression (BGPR) is the answer for modelling two variables that are correlated with each other with discrete data types. The advantage of this data is its ability to handle differences between variances and means (overdispersion) or the opposite (under dispersion). The modelling of this BGPR can be written as shown below.

$$\ln(\mu_{ji}) = \boldsymbol{x_i^T\beta_j} = \beta_{j0} + \beta_{j1}x_{1i} + \beta_{j2}x_{2i} + \cdots + \beta_{jk}x_{ki}$$

$$\mu_{ji} = \exp(\boldsymbol{x_i^T\beta_j}) = \exp\,(\beta_{j0} + \beta_{j1}x_{1i} + \beta_{j2}x_{2i} + \cdots + \beta_{jk}x_{ki}) \quad (1)$$

Where

x_i=$[1 \quad x_{1i} \quad x_{2i} \quad \cdots \quad x_{ki}]^T$

$\beta_i = \left[\beta_{j0} \quad \beta_{j1} \quad \beta_{j2} \quad \cdots \quad \beta_{jk}\right]^T$ $j = 1,2$

$i = 1,2, \ldots, n$ are observations

Simultaneous testing on the BGPR model aims to determine whether the predictor variables simultaneously have a significant effect on the model. The hypothesis used in simultaneous BGPR parameter testing is

$H_o: \beta_{j1} = \beta_{j2} = \cdots = \beta_{j4} = 0$ dan $a_1 = a_2, j = 1,2$

$H_1: at\ least\ \beta_{jk} \neq 0\ dan\ a_1 \neq 0, j = 1,2; k = 1,2,3,4$

The statistical test used is

$$D(\hat{\beta})=-2\left(\frac{L(\omega)}{L(\Omega)}\right) = 2(\ln L(\Omega) - \ln L(\omega)) \quad (2)$$

with:

$L(\Omega)$= likelihood function under population

$$ln\, L(\Omega) = \sum_{i=1}^{n} ln\, \lambda_0 + \sum_{i=1}^{n} ln\, \lambda_0 + \sum_{i=1}^{n} \ln\left(e^{X_i^T \beta_1} - \lambda_0\right) + \sum_{i=1}^{n} \ln\left(e^{X_i^T \beta_2} - \lambda_0\right) - n\lambda_0 + \sum_{i=1}^{n} \ln\left(e^{X_i^T \beta_1} - \lambda_0\right) + \sum_{i=1}^{n} \ln\left(e^{X_i^T \beta_2} - \lambda_0\right) - \sum_{i=1}^{n} y_{1i}\, a_1 - \sum_{i=1}^{n} y_{2i} a_2 + \sum_{i=1}^{n} ln\ W_i$$

Where

$$W_{1i} = \frac{\left(\left(e^{X_i^T \beta_1} - \lambda_0\right) + (y_{1i} - k)\right)^{y_{1i}-k-1}}{(y_{1i}-k)!} exp\big(k(a_1 + a_2 - a_0)\big) \text{ dan } W_{2i} = \frac{\left(\left(e^{X_i^T \beta_2} - \lambda_0\right) + (y_{2i} - k)\right)^{y_{2i}-k-1}}{(y_{1i}-k)!} \frac{(\lambda_0 + k a_0)^{k-1}}{k!}$$

$L(\omega)$ =likelihood function under H_o

$$\ln L(\widehat{\omega}) = \sum_{i=1}^{n} \ln \lambda_0 + \sum_{i=1}^{n} \ln\left(e^{\beta_{1.0}} - \lambda_0\right) + \sum_{i=1}^{n} \ln\left(e^{\beta_{2.0}} - \lambda_0\right) - n\,\lambda_0 + \sum_{i=1}^{n} \ln\left(e^{\beta_{1.0}} - \lambda_0\right) + \sum_{i=1}^{n} \ln\left(e^{\beta_{2.0}} - \lambda_0\right) - \sum_{i=1}^{n} y_{1i} a_1 - \sum_{i=1}^{n} y_{2i} a_2 + \sum_{i=1}^{n} ln\, W_{i.0}$$

Were

$$W_{i.0} = \sum_{k=0}^{\min(y_{1i}, y_{2i})} \{W_{1i.0}, W_{2i.0}\}$$

$$W_{1i.0} = \frac{\left(\left(e^{\beta_{1.0}} - \lambda_0\right) + (y_{1i} - k)\right)^{y_{1i}-k-1}}{(y_{1i}-k)!} exp(k(a_1 + a_2 - a_0)) \text{ and}$$

$$W_{2i} = \frac{\left(\left(e^{X_i^T \beta_2} - \lambda_0\right) + (y_{2i} - k)\right)^{y_{2i}-k-1}}{(y_{2i}-k)!} \frac{(\lambda_0 + k a_0)^{k-1}}{k!}$$

Rejection Area H_o are $D(\hat{\beta}) > \chi^2_{(\alpha-b;\alpha)}$

In the partial hypothesis test, the following is used:

$H_o: \beta_{jk} = 0$

$H_o: at\ least\ \beta_{jk} \neq 0; j = 1,2\ and\ k = 1,2,3,4$

Statistical test

$$Z = \frac{\widehat{\beta}_{jk}}{se(\widehat{\beta}_{jk})} \quad (3)$$

$se(\hat{\beta}_{jk})$ is error standard from β_{jk}. Rejection Area H_0 is $|Z| > Z_{(\frac{\alpha}{2})}$

Parameter α

$H_o: \alpha_j = 0$

$H_o: \alpha_j \neq 0; j = 1,2$

Statistical test

$$Z = \frac{\widehat{\alpha}_j}{se(\widehat{\alpha}_j)}$$

$se(\hat{\alpha}_j)$ Is error standard from $\hat{\alpha}_j$. Rejection area H_0 is $|Z| > Z_{(\frac{\alpha}{2})}$

2.2 Selection of The Best Model

One of the criteria used before performing Bivariate Generalized Poisson Regression analysis is that the dependent variables are not highly correlated, and the dependent variables are distributed according to the bivariate generalized Poisson distribution. The method used is the Akaike Information Criterion (AIC) approach, which is a measure of the relative quality of statistical models of given data for selecting the best model from several existing models. The best regression model is the regression model with the smallest AIC (Ernawati et al., 2023), with the following AIC formula:

$$AICc = AIC + \frac{2k^2+2k}{n-k-1} \quad (4)$$

with $AIC = -2\ln L(\hat{\theta}) + 2k$

$L(\hat{\theta})$ is the maximum value of the likelihood function of the model parameters and k being the number of parameters in the model. The best BGPR model is the model with the smallest AIC value.

2.3 Correlation

According to (Naufal et al., 2026), Statistical techniques to determine the strength of the relationship between the dependent variable (Y) and the independent variable (X) can use correlation with a correlation coefficient that can be defined as follows:

$$r_{xy} = \frac{n\sum XY - (\sum X(\sum Y))}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum x^2 - (\sum x)^2]}} \quad (5)$$

The correlation coefficient can indicate two types of relationships: positive and negative. Where the correlation value ranges from -1 to 1 or can be written as $-1 < r_{xy} < 1$. If the correlation value is close to 1, whether positive or negative, it means that the two variables have a strong linear relationship. A correlation value of zero indicates that the two variables do not have a close linear relationship.

2.4 Multicollinearity

According to (Sihabudin et al., 2021), Multicollinearity is an approach that aims to check for the existence of relationships or associations between independent variables in a regression model. A regression model is considered valid if the independent variables are not significantly correlated with each other. This analysis is performed by considering the tolerance and VIF (Variance Inflation Factor) values as indicators.

$$VIF = \frac{1}{1-R^2} \quad (6)$$

Multicollinearity is performed to ensure that there is no excessive correlation or perfect linear relationship between independent variables in the regression model. Based on the assessment criteria, if the tolerance value is greater than 0.10 and the Variance Inflation Factor (VIF) value is less than 10, then the model is declared free from multicollinearity issues. By contrast, if the tolerance value is equal to or less than 0.10 and the VIF value reaches 10 or more, then the model detects symptoms of multicollinearity that can interfere with the validity of the analysis results.

2.5 Maternal Mortality Rate (MMR)

Maternal Mortality Rate (MMR) is an indicator used to measure the number of female deaths due to complications during pregnancy, childbirth, or within 42 days after childbirth, per 100,000 live births. MMR is one of the important benchmarks in assessing the quality of maternal health services in a country(Tim BAB PPN Loka

Labkesmas Baturaja, 2025). The definition of maternal mortality is classified into two main categories. First, direct causes, which refer to deaths resulting from complications of pregnancy itself. Second, indirect causes, which are deaths triggered by diseases already suffered by the mother and are not a direct result of the reproductive process. Globally, the main factors contributing to maternal mortality include haemorrhage, hypertension in pregnancy (HDK), infection, prolonged labour, and abortion.

2.6 Infant Mortality Rate (IMR)

Infant Mortality Rate (IMR) represents the number of infant deaths under one year of age per 1,000 live births in a one-year period. This indicator serves as a measure of public health quality because it is sensitive to various aspects, ranging from the effectiveness of antenatal services, adequate nutrition for pregnant women, to the success of maternal and child health and family planning programs. In addition, IMR is also influenced by socioeconomic conditions and the quality of the living environment (Pemerintahan dan Pembangunan Manusia Kota Kediri, 2024)

3. Research Method

3.1 Research Design

This study will develop a model for the number of infant and maternal deaths in West Java Province based on influencing factors using a bivariate generalized Poisson regression approach, processed using Microsoft Excel and R software.

3.2 Data Sources and Research Variables

The data used in this study was obtained from the 2024 West Java Health Profile data. Data observed were from 27 districts/cities in West Java. The research variables used in this study consisted of dependent and independent variables. Where the dependent variables are maternal mortality rate (Y_1), and infant mortality rate (Y_2), for the independent variable are percentage of iron supplementation (Fe90) (X_1), Percentage of Childbirth Assisted by Health Workers (X_2), Percentage of visits by pregnant women (K4) (X_3), Percentage of obstetric complications treated (X_4).

3.3 Stages of Research

The stages in this study include several systematic procedures, among which are:

1. Descriptive analysis to describe the characteristics of infant and maternal mortality in West Java Province based on suspected factors using mean values, variance, minimum, and maximum values.
2. Correlation test between infant and maternal mortality in West Java 2024
3. Multicollinearity test using VIF criteria
4. Overdispersion test with Langrange Multiplier
5. Estimate the BGPR model parameters based on the best model using Maximum Likelihood Estimation (MLE) and Newton Raphson iteration.
6. Test simultaneously according to equation (2)
7. Performing partial testing with equation (3)
8. Determine the best model based on the AIC value using equation (4), which is by finding the smallest AIC value from several models that have been obtained.
9. Performing model interpretation

4. Results and Discussion

4.1. Descriptive Analysis

A detailed description of the descriptive statistics for all variables affecting maternal and infant mortality in West Java province is presented in Table 1. Table 1 shows that the average maternal mortality rate in West Java province is 28.3 cases or 28 cases. The variance of maternal mortality in West Java province contains overdispersion, where the average value is higher than the variance. From this data, it can also be seen that the district with the highest maternal mortality rate in 2024 is Bogor. Then, for the number of infant deaths, the average number of infant deaths was 203.74 cases or 204 cases. This mean value is also lower than the variance. From this data, Bogor has the highest number of infant deaths, as seen in the low percentage of pregnant women's visits (K4) in 2024.

Tabel 1. Descriptive Analysis

Variable	Mean	Variance	Minimum	Maximum
Y_1	28.3	410.83	3	105
Y_2	203.74	25663.43	43	824
X_1	89.04	105.38	70.01	108.37
X_2	3.7	7.2	0.31	12.36
X_3	86.8	140.003	67.37	104.4
X_4	109.56	737.41	62.76	169.2

Source: Processed Primary Data, 2026

Tasikmalaya as shown in Table 1, has a low incidence of iron supplementation compared to other areas, with a percentage of 70.01%. This is a concern for the West Java provincial government in preventing maternal and infant mortality and even stunting. The city of Bekasi also has the highest percentage of visits by pregnant women to prevent diseases and/or disorders that can cause disability and/or death. This can be seen from the relatively low number of maternal deaths, but the infant mortality rate is high compared to other districts/cities.

4.2. Correlation and Multicollinearity

Correlation testing between the number of maternal deaths and the number of infant deaths was conducted to determine whether there was a linear relationship between the dependent variable and the correlation value $r_{y_1,y_2} = 0.84$, it means that there is a correlation between the number of maternal deaths and infant deaths in West Java Province in 2024. Furthermore, based on the analysis results, the VIF value for each independent variable was less than 10, as shown in Table 2. Therefore, it can be concluded that no multicollinearity was detected between the predictor variables.

Table 2. Multicollinearity

Independent Variables	VIF	Conclusion
X_1	1.92	No multicollinearity between independent variables
X_2	1.41	
X_3	2.13	
X_4	1.24	

Source: Processed Primary Data, 2026

4.3. Overdispersion Test

Overdispersion was detected in infant and maternal mortality, as indicated by variance values exceeding the mean shown in Table 1. Therefore, testing was conducted to confirm the occurrence of overdispersion using the Lagrange Multiplier test approach. The Lagrange Multiplier test in this study is based on the following series of hypotheses

$H_0: \theta = 0$ (There is no *overdispersion/underdispersion*)

$H_1: \theta \neq 0$ (*overdispersion/underdispersion*)

Table 3. Over/Under Dispersion Test Results

Variable	Dispersion Estimated	P-value
Y_1	2,4196	0,007768
Y_2	4,1782	0,00001469

Source: Processed Primary Data, 2026

Based on the results in Table 3, P-Value obtained for Y_1 is 0.007768 with $\alpha = 0.05$. Comparison of p-value$< \alpha$ is 0.007768 < 0.05 then the decision is rejected H_0, otherwise P-value of Y_2 is 0.00001469 with $\alpha = 0.05$. Comparison of nilai $P - value < \alpha$ 0.0001469<0.05 then the decision is rejected H_0 , now we get conclusion is overdispersion/underdispersion. Therefore, the Bivariate Generalized Poisson Regression (BGPR) model is used as the appropriate analysis method to accommodate these data characteristics. Bivariate regression analysis assumes a linear relationship between two dependent variables.

4.4. Bivariate Generalized Poisson Regression

The results of the examination show that the data is overdispersion, so the Poisson regression model is not appropriate to use. To accommodate these conditions, this study applies the Bivariate Generalized Poisson Regression model.

Table 4. *Bivariate Generalized Poisson Estimated Result*

Parameter	**Coeficient**	**Standard Error**	**Z**	**P-Value**
β_{10}	0.5322	0,1938	2.7464	0.006024
β_{11}	1.9764	0,1559	12.671	0.000000
β_{12}	-0.9910	0,05663	-17.50	0.000000
β_{13}	0.9969	0,04464	22.331	0.000000
β_{14}	1.9048	0.06253	30.462	0.000000
β_{20}	-18.1614	3.6500	-0.049	0.0000028
β_{21}	6.8850	2.3400	0.0293	0.9952
β_{22}	-1.5237	8.8960	-0.0171	0.0341
β_{23}	0.3492	2.9570	0.0118	0,00667
β_{24}	4.1418	1.1850	0.0349	0.9721

Source: Processed Primary Data, 2026

Before conducting the BGPR modelling process, testing will be carried out with simultaneous parameters to determine whether there is at least one variable that affects the model. The hypothesis used for simultaneous testing is

$H_0: \alpha_1 = \alpha_2 \; and \; \beta_{j1} = \beta_{j2} = \cdots = \beta_{j4}$

$H_1: at \; least \; \beta_{jk} \neq 0$ dan $\alpha_j \neq 0 \; j = 1,2$ and $k = 1,2,\cdots,4$

The calculation resulted in a deviation value is 2871 using significant level 5% the result was $\chi^2_{8;0.05} = 15.507$ because the deviation value is greater than $\chi^2_{8;0.05} = 15.507$, the decisions H_0 was rejected, it can be concluded that there is one independent variable that affects the number of maternal and infant deaths in West Java Province in 2024.

To identify which predictor variables, contribute significantly to maternal and infant mortality in West Java Province in 2024. Partial parameter testing was used and the hypotheses used in this test are as follows:

$H_0: \alpha_1 = \beta_{j4} = 0$

$H_1: at \; least \; \beta_{jk} \neq 0$ dan $\alpha_j \neq 0 \; j = 1,2$ and $k = 1,2,\cdots,4$

Level of significance was 95%, so value of $Z_{0,05}$=1,96.

Based on Table 4, it is known that the independent variables that significantly affect the number of maternal deaths in West Java Province are percentage of iron supplementation (Fe90) (X_1), Percentage of Childbirth Assisted by Health Workers (X_2), Percentage of visits by pregnant women (K4) (X_3), Percentage of obstetric complications treated (X_4).

4.5. Akaike Information Criterion (AIC)

The application of the Bivariate Generalized Poisson Regression (BGPR) model in this analysis proved capable of overcoming the problem of overdispersion found in the data on infant and maternal mortality in West Java Province, resulting in more reliable parameter estimates. Therefore, the best model will be determined based on the smallest AIC value according to Table 5.

Table 5. Comparison of the best models with AIC

Independent Variables	**AIC**	**Independent Variables**	**AIC**
X_1	453.14	$X_2 + X_3$	223.98
X_2	223.51	$X_2 + X_4$	220.45
X_3	419.47	$X_3 + X_4$	421.92
X_4	461.31	$X_1 + X_2 + X_3$	215.79
$X_1 + X_2$	223.83	$X_1 + X_2 + X_4$	221.4
$X_1 + X_3$	421	$X_2 + X_3 + X_4$	217.81
$X_1 + X_4$	452.7	$X_1 + X_2 + X_3 + X_4$	210.15

Source: Processed Primary Data, 2026

Based on the AIC criteria for each possible model for bivariate generalized Poisson regression based on the selection of independent variables used, the smallest AIC value was obtained for the main variable, which is percentage of iron supplementation (Fe90), Percentage of Childbirth Assisted by Health Workers, Percentage of visits by pregnant women (K4), Percentage of obstetric complications treated.

4.6. Modelling Maternal Mortality Rates

Results of the estimation process obtained the form of a Bivariate Generalized Poisson Regression (BGPR) model for the maternal mortality variable (Y_1) with significance variable are percentage of iron supplementation (Fe90) (X_1), Percentage of Childbirth Assisted by Health Workers (X_2), Percentage of visits by pregnant women (K4) (X_3), Percentage of obstetric complications treated (X_4).

$$\ln(\lambda_1) = 0.5322 + 1.9764X_1 - 0.9910X_2 + 0.9969X_3 + 1.9048X_4$$

The statistical test results show that $p - value < \alpha = 0.05$, which means that there is a significant relationship between the four independent variables. Then model can illustrate that for every 1 percent increase in the percentage of iron supplementation (Fe90) (X_1) the average number of maternal deaths will increase $\exp(1.9764) = 7.22$ times assuming all other variables remain constant. For every 1 percent increase percentage of childbirth assisted by health workers (X_2) the average number of maternal deaths will decrease by $\exp(0.9910) = 2.69$ times assuming all other variables remain constant. Furthermore, the higher the number Percentage of visits by pregnant women (K4) (X_3) for every 1 percent then the average number of maternal deaths will increase by $\exp(0.9969) = 2.71$ times assuming all other variables remain constant. Every increase in percentage of obstetric complications treated (X_4) by 1 percent, the average number of maternal deaths will increase by $\exp(1.9048) = 6.72$ times, assuming all other variables remain constant.

4.7. Modeling Infant Mortality Rates

Result of the estimation process obtained the form of a Bivariate Generalized Poisson Regression (BGPR) model for infant mortality rates (Y_2) with significance variables are Percentage of childbirth Assisted by Health workers (X_2) and Percentage of visits by pregnant women (K4) (X_3).

$$\ln(\lambda_2) = -18.16 - 1.52337X_2 + 0.3492X_3$$

Statistical test results show that $p - value < \alpha = 0.05$, which means that there is a significant relationship between two independent variables. The interpretation of this model can be explained as follows: for every one percent decrease in the percentage of deliveries attended by health workers (X_2), there will be a decrease in the average number of infant deaths by exp (1.52337) =0.218 times the previous condition. Continue to increase the percentage of visits by pregnant women (K4) (X_3) by 1 percent so the average of infant deaths will increase exp (0.3492) =1.42 times assuming all other variables remain constant. From the modeling results using the BGPR approach, a correlation was found between health service factors and maternal and infant mortality rates. This confirms that the presence of professional medical personnel during the birth process is an important intervention to reduce the risk of maternal fatalities in West Java. This is in line with (Sari et al., 2023) that providing training for healthcare providers ensures that healthcare workers can ensure mothers receive professional assistance when health risks arise during childbirth. Then, it is recommended that the West Java Health Office collaborate with community health centers, midwives, or health volunteers to provide more extensive education on the importance of taking iron tablets (Fe90) to prevent acute anemia, which is one of the triggers of postpartum hemorrhage. The community is also encouraged to optimize the use of the K4 program as a preventive measure. Through the medical examinations available in this program, the health conditions of mothers and fetuses can be monitored in depth, enabling potential risks during pregnancy to be detected as early as possible.

5. Conclusion

Based on the results obtained, it can be concluded that the analysis shows a general description of the data, which is average maternal mortality rate in West Java Province is 28.3, with the highest number occurring in Bogor, 105 cases, and the lowest number occurring in Banjar Regency. Meanwhile, the average number of infant deaths in West Java Province is 203.74, with the highest number occurring in Bogor 824 cases, and the lowest number occurring in Pangandaran 43 cases.

The results of testing the Bivariate Generalized Poisson Regression model parameters show that for the maternal mortality model, the variables that have a significant effect are percentage of iron supplementation (Fe90), Percentage of Childbirth Assisted by Health Workers, Percentage of visits by pregnant women (K4), Percentage of obstetric complications treated. Then, for the infant mortality model, the significant variables were Percentage of childbirth Assisted by Health workers and Percentage of visits by pregnant women (K4).

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