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Analysis of Factors that Influence Maternal Mortality Rates Using Generalized Poisson Regression

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ABSTRACT

Maternal mortality rate (MMR) refers to the number of deaths of women within 42 days after childbirth or during pregnancy. This study aims to identify factors affecting MMR in East Java and compare the performance of the generalized Poisson regression (GPR) model with the Poisson regression. The method used was GPR, a regression model designed for count data that extended Poisson regression to overcome the problem of overdispersion or underdispersion. This method was applied to data derived from the East Java Health Office, including MMR as the dependent variable, as well as five variables hypothesized to affect MMR in 38 districts/cities. Results showed that the GPR model outperformed the Poisson regression, as indicated by a lower AIC value of 239.515, in identifying the factors influencing MMR. Factors such as delivery handled by health workers, K6 visits by pregnant women, provision of diphtheria-tetanus immunization, and obstetric complications were found to affect MMR in East Java in 2022.

1. Introduction

Mortality rate is the average number of deaths of people in a place in a given time. In simple terms, it is the number of deaths due to disease or natural death. The mortality rate is important for assessing public health in a particular country or place. In many places, the lack of medical personnel, treatment facilities, and equipment, forcing people to opt for conventional medicine, and also the lack of knowledge about first aid measures to deal with accidents results in a higher mortality rate in a region [1]–[3]. According to the World Health Organization (WHO), maternal mortality rate (MMR) is the death of a woman during pregnancy or 42 days after delivery, regardless of the cause of death [4]. Globally, the MMR in 2022 was estimated to be 287,000 per 100,000 live births. Meanwhile, the MMR in Indonesia showed a decline, decreasing from 7,389 per 100,000 live births in 2021 to 3,572 in 2022. In 2021, East Java had the highest mortality rate, but this number experienced a reduction by 2022 [5].

The millennium development goals (MDGs) declaration, followed by the sustainable development goals (SDGs) declaration, aims to address future challenges and support sustainable development. One of the targets is for the maternal mortality rate (MMR) to fall below 70 per 100,000 live births by 2030. In 2021, East Java's MMR was recorded at 234.7 per 100,000 live births, falling to 93 per 100,000 live births in 2022. Although lower than the national MMR, the MMR in East Java still has not reached the target in the health sector, namely Long-Term Health Development Plan in 2005–2025, which targets 74 per 100,000 live births. According to Prof. Budi Santoso, Dean of Airlangga University, although the MMR has decreased, it is necessary to conduct early detection during pregnancy and collaborate with various parties to improve human resources and health services to reduce maternal mortality [6].

Previous research on MMR revealed that the Poisson regression model used in the analysis faced the problem of overdispersion, where the variance is greater than the mean. To address this limitation, use of generalized Poisson regression (GPR) to handle overdispersion was recommended, with the factors found to be influential being health workers and the number of health centers [7], [8]. The application of GPR demonstrated superior performance compared to Poisson regression, with delivery by a health worker identified as a significant factor influencing MMR [9]. Blood supplementation (Fe) tablets and regular health care visits during pregnancy are important to meet maternal nutritional needs, thereby reducing MMR [10]. Tetanus toxoid diphtheria (Td) immunization for women of childbearing age is an effective approach to reducing MMR during the COVID-19 pandemic [11]. The program for birth planning and complication prevention (*program perencanaan persalinan dan pencegahan komplikasi*, P4K) at the Yogyakarta health center plays a role in assisting childbirth [12].

The number of maternal deaths, which constitutes count data, is the focus of this study. Therefore, an appropriate analytical method is regression analysis, aimed at identifying other variables that influence maternal mortality. In general, regression analysis is commonly used for continuous response variables. However, in many practical cases, the response variable is discrete (count data), making Poisson regression a more suitable method. Nevertheless, the Poisson regression model assumes that the mean and variance of the data are equal, whereas in reality, maternal mortality data often exhibit overdispersion or underdispersion. Previous studies have not evaluated this assumption, potentially leading to biased estimation results. For this reason, the present study employs the GPR model as an alternative capable of addressing such dispersion issues. The novelty of this study lies in the application of the GPR model to maternal mortality data at the district/city level in East Java Province, which has rarely been explored in previous research [13].

2. The Proposed Method

2.1. Data

The data used in this study are secondary data obtained from the East Java Health Profile Report for the year 2022. The research unit comprised 38 districts/cities [14]. The variables used in the study are presented in Table 1.

Table 1. Research Variables

Variables	Description	Data Types	unit of analysis
Y	Number of Maternal Deaths	Discrete	Count (cases)
X_1	Number of Health Workers	Continuous	Count (cases)
X_2	Health Services (k6)	Continuous	Count (cases)
X_3	Immunization administration td	Continuous	Count (cases)
X_4	Take Blood Addition Tablets	Continuous	Count (cases)
X_5	Obstetric Complications	Continuous	Count (cases)

Source: [13]

After collecting data, the next stage was processing the data. The stages used to obtain the factors that influence the number of stunting can be explained in Fig. 1. The research stages, based on the research flowchart in Figure 1, are described as follows:

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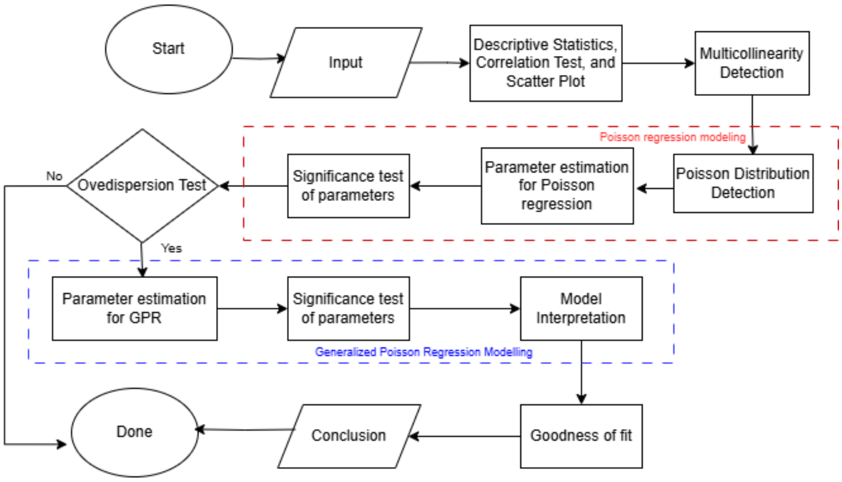

Fig 1. Flowchart of generalized Poisson regression.

2.2. Preliminary Analysis

2.2.1. Correlation

Correlation is a measure to assess the magnitude of the linear relationship between two variables [15]. The hypothesis for testing the significance of the correlation coefficient is as follows.

$H_0: \rho = 0$ (there is no relationship between variables *X* and *Y*)

$H_1: \rho \neq 0$ (there is a relationship between *X* and *Y*)

Test Statistic

$$r_{(xy)} = \frac{n\sum_{i=1}^{n} x_i y_i - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} y_i}{\sqrt{\left[n\sum_{i=1}^{n} x_i^2 - \left(\sum_{i=1}^{n} x_i\right)^2\right]\left[n\sum_{i=1}^{n} y_i^2 - \left(\sum_{i=1}^{n} y_i\right)^2\right]}} \quad (1)$$

The correlation coefficient can reflect two types of positive and negative relationships because the value is in the correlation range close to 1, both in the direction can be written as $-1 \leq ry, x \leq 1$, indicating a strong linear relationship between the variables.

2.2.2. Multicollinearity

Multicollinearity is a condition in regression analysis where two or more independent variables have a high correlation between their variables. This indicates a strong relationship between the predictor variables. This can be proven by looking at the variance inflation factor (VIF) value greater than 10 or a tolerance value of less than 0.10 [16]. The VIF value is represented as:

$$VIF_j = \frac{1}{1 - R_j^2} \quad (2)$$

where R_j^2 denotes coefficient of determination of the auxiliary regression.

Auxiliary regression is a regression where X_j is the response variable, and the other *X* is the predictor variable.

2.3. Method

2.3.1. Poisson Distribution

Dependent discrete random variables follow a Poisson distribution. Furthermore, if t is a specific period and μ is the average occurrence per unit time, then the average *y* is μt. The probability of an experiment in a fast period or a small area has the same probability as the time or area. It is independent of the fact that most of the experiment's outcomes occur outside of the time or location. The probability function is

$$P(x) = \frac{e^{-\lambda}\lambda^x}{x!} \quad (3)$$

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where λ denotes incidence rate (average incidence) and *x* denotes number of successful elements in the sample or discrete random variable.

2.3.2. Poisson Regression

Nonlinear regression analysis for Poisson distribution is known as Poisson regression, which usually uses discrete data [18]. The Poisson regression model, the generalized linear model (GLM), assumes the response data are Poisson distributed [19]. This model is shown below.

y_i = Poisson (μ_i)

μ_i = exp($x_i{}^T\beta$)

then

$$\ln(\mu_i) = x_i{}^T\beta = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_k x_{ki} \quad (4)$$

$$\mu_i = \exp(x_i{}^T\beta) = \exp(\beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_k x_{ki}) \quad (5)$$

where β_0 is the intercept (constant) in the model; $\beta_1, \beta_2, \ldots \beta_k$ is regression coefficients for each independent variable; $x_{1i}, x_{2i}, \ldots, x_{ki}$ are values of the independent variables for the observation; and k is the number of independent variables

The following MLE method estimates the Poisson regression model. Equation (6) is the Poisson regression model with a log function.

$$\ln L(\beta) = -\sum_{i=1}^{n} \exp(x_i{}^T\beta) + \sum_{i=1}^{n} y_i x_i{}^T\beta - \sum_{i=1}^{n} \ln(y_i!). \quad (6)$$

Poisson regression is considered to have overdispersion if the variance value of the data > the mean value. Underdispersion occurs when the variance is less than the mean, and the predictors are sparse. In cases where overdispersion occurs, and parameters are calculated using Poisson regression, the results will be inefficient as the standard error becomes smaller. The log-fitted Poisson regression model is beautiful for Poisson regression as it ensures that all values of the predicted response variable will be nonnegative. The overdispersion condition can be written as *var(Y)>E(Y)* or with a value of $\alpha > 1$ [9].

2.3.3. Generalized Poisson Regression

The response variable, which follows a Poisson distribution, is modeled using the GLM framework. It follows the distribution of the exponential family, the Poisson distribution. There is no multicollinearity problem, and the variance is proportional to the mean based on the correlation values of the predictor variables. However, Poisson regression becomes less efficient if the data have overdispersion or underdispersion, so a more appropriate model method is needed to handle these conditions is GPR [13]. The following generalized Poisson distribution has a probability function:

$$f(y_i, \mu_i, \alpha) = \left(\frac{\mu_i}{1+\alpha\mu_i}\right)^{yi} \frac{(1+\alpha y_i)^{y_i-1}}{y!} \exp\left(\frac{-\mu_i(1+\alpha y_i}{1+\alpha\mu_i}\right) \quad (7)$$

with *i* = 1,2,… and $\mu_i = \mu_i(x_i) = \exp(x_i{}^T\beta)$

where x_i is vector of predictor variables and β is vector of regression parameters.

GPR models, such as Poisson and GLM models, assumes that the random components follow a generalized Poisson distribution. The probability function corresponds to (7).

$$\ln(\mu_i) = x_i{}^T\beta = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_k x_{ki} \quad (8)$$

$$\mu_i = \exp(x_i{}^T\beta) = \exp(\beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_k x_{ki}) \quad (9)$$

It is assumed that the MLE method is used to parameterize the standard Poisson regression, which means maximizing the likelihood function of the parameters (α, β). The likelihood function of GPR is:

$$L(\alpha, \mu) = \prod_{i=1}^{n} \left[\frac{\mu_i}{1+\alpha\mu_i}\right]^{yi} \frac{(1+\alpha y_i)^{y_i-1}}{y!} \exp\frac{-\mu_i(1+\alpha\mu_i)}{1+\alpha\mu_i} \quad (10)$$

The *ln* likelihood function of GPR is

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$$Ln\, L(\alpha,\beta) = \sum_{i=1}^{n}\left\{y_i\, ln\left[\frac{\mu_i}{1+\alpha\mu_i}\right] + (y_i - 1)\, ln(1+\alpha y_i) - ln(y_i!) - \frac{\mu_i(1+\alpha y_i)}{1+\alpha\mu_i}\right\} \quad (11)$$

$$ln\, L(\alpha,\beta) = \sum_{i=1}^{n}(y_i\, ln(exp(x_i{}^T\beta)) - y_i ln\ (x_i{}^T\beta)) + (y_i - 1)\, ln(1+\alpha y_i)) - \sum_{i=1}^{n}\left(ln(y!) - \frac{exp(x_i{}^T\beta)(1+\alpha y_i)}{1+\alpha\, exp(x_i{}^T\beta)}\right) \quad (12)$$

Significance test using the maximum estimation ratio test simultaneously with the following test statistics:

$$D(\hat{\beta}) = -2\ln\left[\frac{L(\widehat{\omega})}{L(\widehat{\Omega})}\right] = 2\left[\ln\left(L(\widehat{\omega})\right) - \ln L(\widehat{\Omega}))\right] \quad (13)$$

Partial significance test using maximum likelihood ratio test with the following test statistics:

$$z = \frac{\widehat{\beta}_j}{se\ (\widehat{\beta}_j)} \quad (14)$$

where $se\ (\hat{\beta}_j)$ is the error rate of β_j.

2.3.4. Model Accuracy Rate

a. Akaike Information Criteria

The Akaike information criteria (AIC) method is the best method to determine the regression model. It is based on the maximum likelihood estimation (MLE) method and aims to find the GPR model by finding the AIC value. This method is one of the methods to select the best regression model [9].

$$AIC = -2\ln L(\beta) + 2k \quad (15)$$

where $L(\beta)$ is the likelihood value and k is the number of parameters. The best regression model is the one that produces the smallest AIC value.

b. Root Mean Square Error

The root mean square error (RMSE) is a common metric used to measure the accuracy of a regression model by calculating the square root of the average of the squared differences between the observed values and the predicted values.

3. Results and Discussion

This chapter presents the results of data analysis and discussion, focusing on the identification of factors influencing maternal mortality based on the applied models. The analysis includes evaluating model fit, interpreting significant parameters, and comparing the performance of the Generalized Poisson Regression model with the Poisson regression model.

3.1. Descriptive Analysis

Descriptive statistics consist of various techniques used to describe and analyze data. This includes measures of central tendency, measures of dispersion, and data visualization through graphs, as shown in Fig. 2 and Table 2.

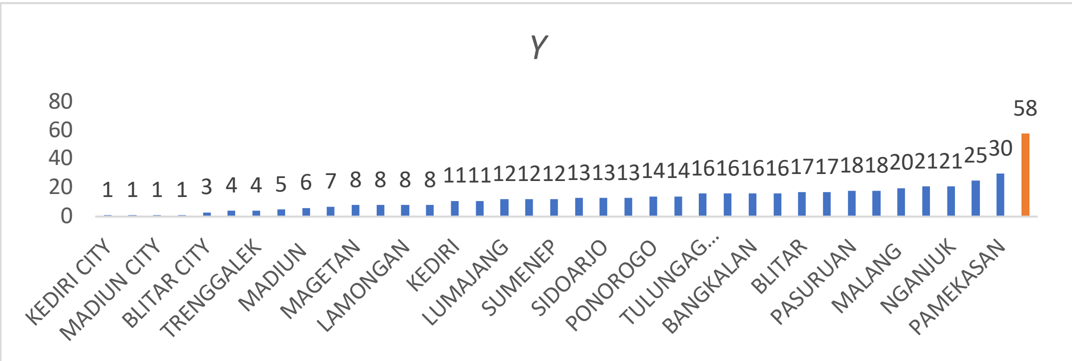

Fig 2. Maternal mortality rate in East Java Province.

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Table 2. Descriptive Analysis

Variables	Mean	Minimum	Maximum	Variance
Y	13	1	58	1.041174×10^2
X_1	492	47	1183	7.223810×10^4
X_2	14825	1271	43402	1.010274×10^8
X_3	11377	3630	178468	8.681760×10^7
X_4	10369	127	37871	7.743385×10^7
X_5	1694	0	13260	6.749162×10^6

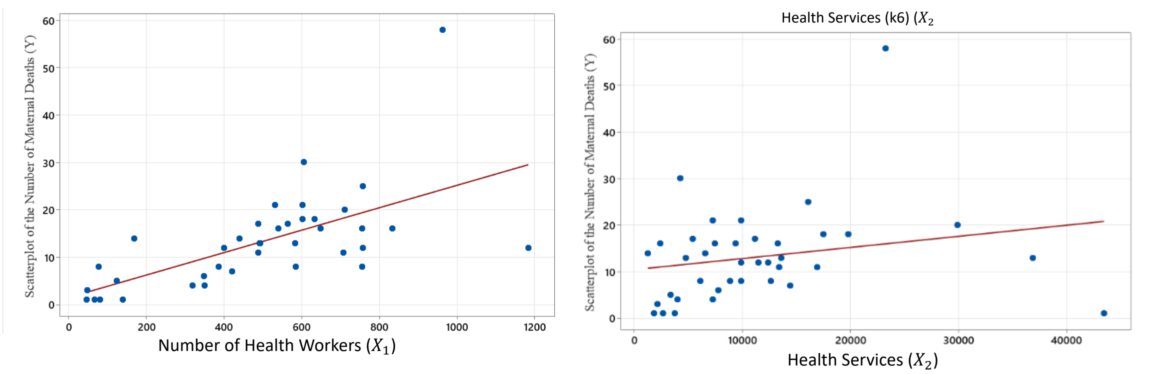
Based on Fig. 2, the highest maternal mortality rate in 2022 is in Jember district, which is 58 deaths, while the lowest mortality rate is in four cities in East Java province, with 1 case of death each. As shown in Table 2, the mean of maternal mortality is 13, and the mean number of health workers at the health center is 1,136. Among the observed region, the Sumenep district has the most significant number of 1,183 health workers, whereas Blitar City has the lowest number of health workers, with only 48 workers.

3.2. Correlation Test

Table 3 presents the correlation, which measures the strength of the linear relationship between two variables. Identification of the relationship between the dependent variable (*Y*) and the independent variables (*X*) can be conducted using a scatter plot. The relationship between variables is illustrated in Fig. 3, which shows a scatter plot used to observe the pattern of correlation. This pattern may indicate a positive, negative, or no correlation between the variables.

Table 3. Correlation Between Variables

		X_1	X_2	X_3	X_4	X_5	Y
X_1	Pearson Correlation	1	0.222	0.367*	0.307	0.206	0.624**
	Sig. (2-tailed)		0.181	0.023	0.061	0.216	0.000
X_2	Pearson Correlation	0.222	1	0.347*	0.406*	0.404*	0.218
	Sig. (2-tailed)	0.181		0.033	0.011	0.012	0.188
X_3	Pearson Correlation	0.367*	0.347*	1	0.526**	0.202	0.330*
	Sig. (2-tailed)	0.023	0.033		0.001	0.224	0.043
X_4	Pearson Correlation	0.307	0.406*	0.526**	1	0.426**	0.318
	Sig. (2-tailed)	0.061	0.011	0.001		0.008	0.052
X_5	Pearson Correlation	0.206	0.404*	0.202	0.426**	1	0.496**
	Sig. (2-tailed)	0.216	0.012	0.224	0.008		0.002
Y	Pearson Correlation	0.624	0.218	0.33	0.318	0.496	1
	Sig. (2-tailed)	0.000	0.188	0.043	0.052	0.002	



(a) (b)

Fig 3. Scatter plot of dependent and independent variables, (a) scatterplot of the number of maternal deaths (y) vs number of health workers (X_1), (b) scatterplot of the number of maternal deaths (y) vs health services (k6) (X_2).

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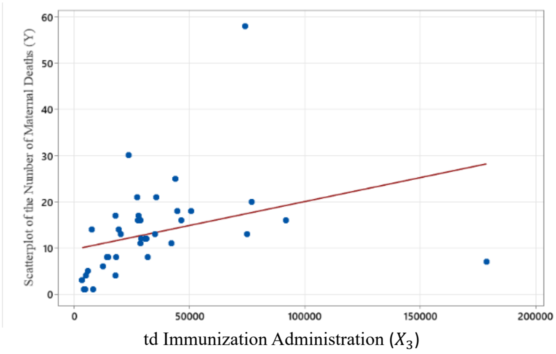
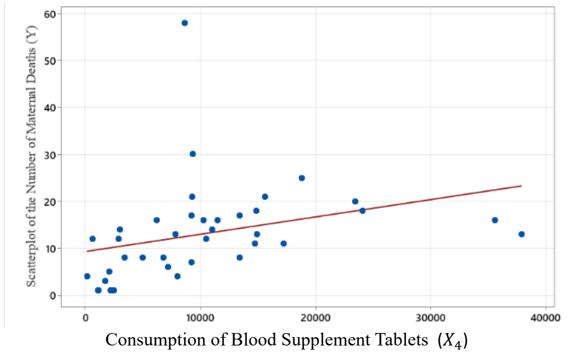
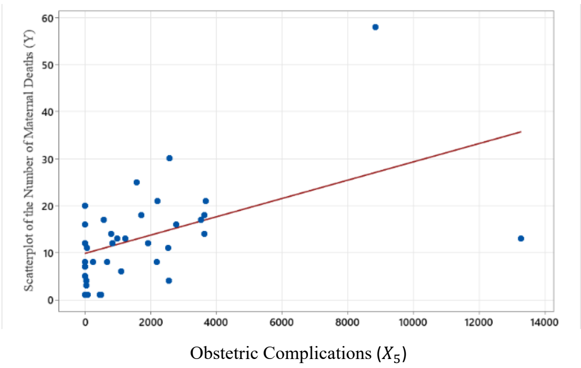


(c)



(d)



(e)

Fig 3. (*Continued*) Scatter plot of dependent and independent variables, (c) scatterplot of the number of maternal deaths (y) vs immunization administration td (X_3), (d) scatterplot of the number of maternal deaths (y) vs take blood addition tablets (X_4), and (e) scatterplot of the number of maternal deaths (y) vs obstetric complications (X_5).

Table 3 shows that there is a correlation between maternal mortality rate and the number of health workers (X_1), provision of td immunization (X_3), and obstetric complications (X_5), while K6 health services (X_2) and consumption of blood supplement tablets (X_4) have no relationship with maternal mortality rate. The number of health workers (X_1) has a stronger relationship than other factors. As shown in Table 3 and in Figure 3, there is a positive relationship between the maternal mortality rate (Y) the variables presumed to influence it. If the number of health workers (X_1), K6 health services (X_2), provision of Td immunization (X_3), consumption of blood supplement tablets (X_4), and obstetric complications (X_5) increase, the maternal mortality rate will also increase. In addition, the dot plots indicate the presence of outlier data in all relationship patterns and indicate clustered data with accompanying spatial effects.

3.3. Multicollinearity Detection

Multicollinearity is a condition in regression analysis where two or more independent variables have a high correlation between their variables. This can be proven by looking at the VIF value greater than 10 or a tolerance value of less than 0.10 [16], as shown in Table 4.

Table 4. Multicollinearity Detection

Predictor Variables	Number of Health Workers	Health Services (K6)	td Immunization	Consumption of Blood Supplement Tablets	Obstetric Complications
VIF	1.94	4.53	2.25	3.27	1.99

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Table 4 shows no multicollinearity between the independent variables because the VIF value is < 10. This proves that all the selected predictor variables are suitable for modeling.

3.4. Poisson Regression

The method known as Poisson regression uses the Poisson distribution to model the counting of variable data that falls under the category of discrete data.

3.4.1. Poisson Distribution Fit Detection

Fig. 4 presents the detection of data suitability with a Poisson distribution for the dependent variable, namely the number of maternal deaths in East Java Province in 2022. This detection was carried out using a histogram plot to observe whether the distribution of the count data resembles the characteristics of a Poisson distribution.

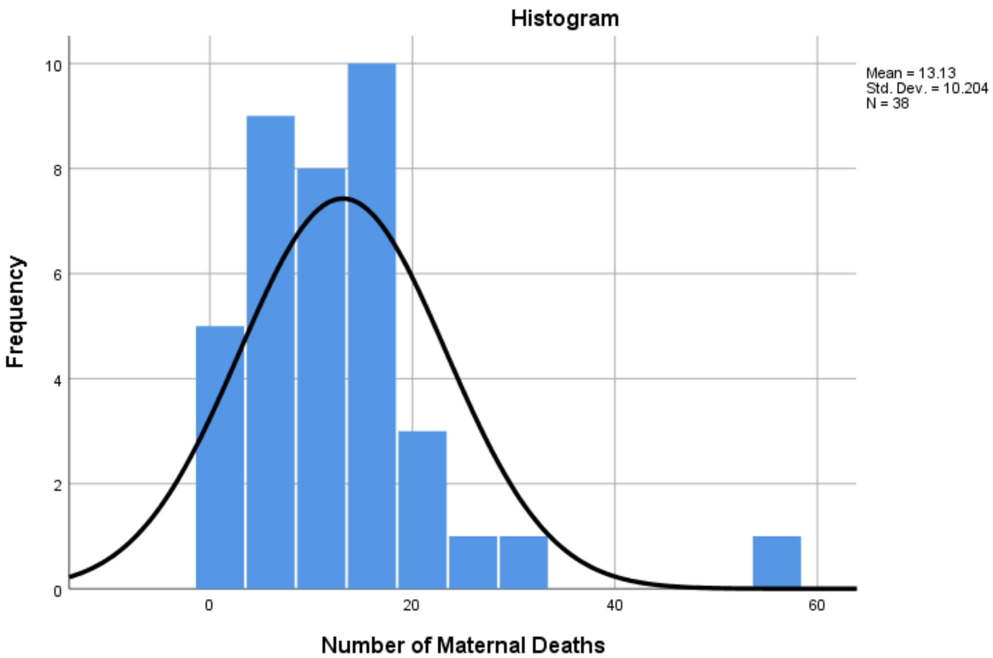

Fig 4. Identification of Poisson distribution plot.

As shown in Fig. 4, the distribution of maternal mortality data are not symmetrical around the mean, and there is skewness to the right, indicating that the data are not normal. This result indicates random events that are independent of each other and have a constant probability of occurring within a specific time interval. Mortality data are counted on a discrete scale, fulfilling the Poisson distribution.

3.4.2. Testing the Significance of Poisson Regression Parameters Simultaneously

A simultaneous test is a statistical method used to examine whether several coefficients or variables in a regression model collectively have a significant effect on the dependent variable. The results of this test can be seen in Table 5. The hypothesis that was used in this test is the following.

$H_0: \beta_1 = \beta_2 = \cdots = \beta_5 = 0$ (independent variables simultaneously do not affect the dependent variable)

H_0There is at least one $\beta_k \neq 0; k = 1,2,3,4,5$ (independent variables simultaneously affect the dependent variable)

Table 5. Concurrent Poisson Regression Test Statistics

Likelihood Ratio Chi-Square	df	p-Value
170.901	5	0.00

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Based on Table 5, the likelihood ratio chi-square (G) is 0.00, indicating the rejection of H0. It means that there is at least one independent variable that affects maternal mortality in East Java Province because G > ${X^2}_{0.05;5}$ and p-value < α, namely $170.901 > 11.07$ and 0.00 < 0.05.

3.4.3. Partial Parameter Significance Testing

Parameter testing was conducted partially to evaluate each parameter individually. The results of this test can be seen in Table 6. The hypothesis was used in this test is the following.

$H_0: \beta_k = 0$

$H_1: = \beta_k \neq 0; k = 1,2,3,4,5$

Table 6. Partial Poisson Regression Test Statistics

Parameters	Estimation	Standard of Error	Z_{count}	p-Value
Constants	1.480	1.380×10^{-1}	10.729	2×10^{-16}
β_1	1.383×10^{-3}	2.459×10^{-4}	5.626	1.84×10^{-8}
β_2	3.085×10^{-5}	8.671×10^{-6}	3.558	0.000373
β_3	-2.154×10^{-5}	7.520×10^{-6}	-3.434	0.000827
β_4	-6.163×10^{-6}	8.184×10^{-6}	-0.753	0.451379
β_5	7.825×10^{-5}	1.804×10^{-5}	4.338	1.44×10^{-5}

Base on Table 6, since H_0 is rejected when the value of $|Z_{count}| > Z_{\alpha/2}$ or $p - value < \alpha$ (0.05), it can be concluded that several X variables affect the Y variable, namely the number of health workers (X_1), health services (K6) (X_2), td immunization (X_3) and obstetric complications (X_5). The following model was formed from the Poisson regression method on maternal mortality in East Java in 2022.

$\hat{\mu} = \exp\,(\ 1.480 + 1.383 \times 10^{-3} X_1 + 3.085 \times 10^{-5} X_2 + -2.154 \times 10^{-5} X_3 + 7.825 \times 10^{-5} X_5)$

3.5. Overdispersion

Overdispersion is a condition in count data models such as the Poisson regression, where the observed variance is greater than the mean, violating the basic assumption of the Poisson distribution that the mean and variance are equal, as shown in Table 7.

Table 7. Pearson Chi-Square Values and Deviation

	Value	DB	Dispersion Estimation
Deviation	256.352	37	6.928
Pearson chi-square	95.339	32	2.979

Table 7 shows that the data on maternal deaths show overdispersion because the estimated dispersion value is greater than 1. Therefore, the data were further analyzed using GPR.

3.6. Generalized Poisson Regression

Although the GPR model is similar to the Poisson regression model, its random component is generally considered Poisson distributed.

3.6.1. Testing Generalized Poisson Regression Parameter Significance Simultaneously

A simultaneous test is a statistical method used to examine whether several coefficients or variables in a regression model collectively have a significant effect on the dependent variable. The results of this test can be seen in Table 8. The hypothesis that was used in this test:

$H_0: \beta_1 = \beta_2 = \cdots = \beta_5 = 0$ (independent variables simultaneously do not affect the dependent variable)

H_1There is at least one $\beta_k \neq 0; k = 1,2,3,4,5$ (independent variables simultaneously affect the dependent variable)

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Table 8. Simultaneous Generalized Poisson Regression Test

Likelihood Ratio Chi-Square	df	p-Value
40.630	5	0.000

Based on Table 8, the G value shows rejection of H_0. This result indicates that at least one independent variable highly influences the dependent variable because the value shows significance. G > ${x^2}_{0.05;5}$ and p-value < 0.05, namely $40.630 > 11.07$ and 0.00 < 0.05.

3.6.2. Partial Parameter Significance Testing

Parameter testing is conducted partially to evaluate each parameter individually. The results of this test can be seen in Table 9. The hypothesis was used in this test:

$H_0: \beta_j = 0$

$H_1: = \beta_k \neq 0; k = 1,2,3,4,5$

Table 9. Partial Generalized Poisson Regression Test

Parameters	Estimation	Standard Error	Z_{count}	p-Value
Constants	1.053	2.248×10^{-1}	4.683	2.83×10^{-6}
β_1	1.0340×10^{-3}	3.659×10^{-4}	3.662	**0.00025**
β_2	3.196×10^{-5}	1.310×10^{-5}	2.440	**0.01470**
β_3	-2.240×10^{-5}	1.102×10^{-5}	-2.032	**0.04213**
β_4	-7.172×10^{-6}	1.232×10^{-5}	-0.582	0.56062
β_5	7.177×10^{-5}	2.679×10^{-5}	2.679	**0.00738**

Based on Table 8, H_0 is rejected when the value of $|Z_{count}| > Z_{\alpha/2}$ or $p - value < \alpha$ (0.05); this proves that severeal X variables affect the Y variable, namely the number of health workers (X_1), health services (K6) (X_2), td immunization (X_3), obstetric complications (X_5). The positive relationship between the number of health workers (X_1) and health services (X_2) with MMR is most likely due to a reverse causality phenomenon, in which areas with high MMR are prioritized for the addition of health workers and services as a form of intervention. At the same time, the consumption of blood supplement tablets (X_4) has no effect because it has a value of $\alpha < 0.05$. The following model has been formed from the GPR method on maternal mortality in East Java in 2022.

$\hat{\mu} = \exp\left(1.053 + 1.0340 \times 10^{-3} X_1 + 3.196 \times 10^{-5} X_2 - 2.240 \times 10^{-5} X_3 + 7.177 \times 10^{-5} X_5\right)$

GPR is an extension of the standard Poisson regression that addresses situations where the assumption of equal mean and variance does not hold. Unlike the standard Poisson model, GPR introduces a dispersion parameter that allows it to handle both overdispersion and underdispersion, making it more flexible for modeling count data with heterogeneous variability. This added flexibility makes GPR particularly suitable for analyzing maternal mortality data, where count variability often deviates from the strict assumptions of the traditional Poisson model.

3.7. Model Accuracy Rate

The AIC method is the best method to determine the regression model. It is based on the MLE method. The AIC test aims to find the GPR model by finding the AIC value. RMSE is a common metric used to measure the accuracy of a regression model by calculating the square root of the average of the squared differences between the observed values and the predicted values, as shown in Table 10.

Table 10. Akaike Information Criteria

Methods	Akaike Information Criteria (AIC)	RMSE
Poisson regression	253.561	5.578
Generalized Poisson regression	239.515	1.257

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Based on Table 10, the GPR method is better than Poisson regression. This is evidenced by the lower AIC value in the GPR method, 239.515, compared to Poisson regression, which has an AIC value of 253.561. In addition, similar results were also found in research on diphtheria cases, where the Poisson regression method was initially used but experienced overdispersion. The problem was then addressed with GPR, which provided better results than Poisson regression [20]. Based on the RMSE values, the GPR model, with RMSE of 1.26, provided better predictive results compared to the standard Poisson regression model RMSE of 5.58. This result indicates that the GPR model is more capable of capturing the variability in maternal mortality data in East Java.

4. Conclusion

Based on the results and discussion, it can be concluded that factors significantly affecting the MMR in East Java province in 2023 using the GPR method are childbirth handled by health workers (X_1). These health services mean K6 visits by pregnant women (X_2), provision of td immunization (X_3), and obstetric complications (X_5). The GPR method is more appropriate for identifying factors affecting mortality rates in East Java in 2022 than the Poisson regression model because it produces a smaller AIC and RMSE value.

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