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Bayesian Generalized Poisson Regression Modeling for Overdispersed Maternal Mortality Data

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Abstract. Maternal mortality is a global health issue that reflects disparities in access to and the quality of healthcare services. This study applies the Bayesian Generalized Poisson Regression (BGPR) approach to address the problem of overdispersion in the data, which renders the standard Poisson regression model less appropriate. The Generalized Poisson model was chosen for its ability to handle overdispersion, while the Bayesian approach provides more stable parameter estimates, particularly when working with small sample sizes. The analysis results show that all independent variables have a statistically significant effect on maternal mortality. In addition, the BGPR model yields a lower Bayesian Information Criterion (BIC) value compared to the standard Poisson model, indicating better model performance. The BGPR model helps identify the key factors that truly contribute to maternal mortality, making the results useful for local governments or health institutions in setting priorities for intervention.

Keywords: Bayesian statistics, Maternal health, Maternal mortality rate, Overdispersion, Statistical modeling

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1. Introduction

Maternal Mortality Ratio (MMR) is a key indicator of a country's healthcare quality and societal well-being. According to WHO (2023), over 800 women die daily from pregnancy or childbirth complications, mostly in developing countries [1]. Indonesia, as one of the most populous nations, still faces major challenges in reducing MMR to meet the 2030 SDGs target of below 70 deaths per 100,000 live births [2]. The maternal mortality rate (MMR) in Indonesia, particularly in NTT Province, remains high and is a serious concern in efforts to improve the quality of maternal healthcare services. Despite various interventions implemented by the government through national programs, such as the Maternity Insurance (Jampersal), increased coverage of antenatal care visits (K1 and K4), and training of healthcare workers, the decline in MMR has been slow and uneven across regions [3].
using Microsoft Office Word format (not .pdf). The full paper should be submitted as Microsoft Office Word (.doc or .docx) file.

Poisson regression is a commonly used statistical method for analyzing count data. However, its key

assumption—that the mean is equal to the variance—is often violated in maternal mortality data due to the presence of overdispersion[4]. To overcome this limitation, various alternative approaches have been developed, one of which is the Generalized Poisson Regression (GPR). This model offers greater flexibility in handling both overdispersion and underdispersion without requiring a drastic change to the underlying distribution. [5]. Generalized Poisson Regression (GPR) usually uses Maximum Likelihood Estimation (MLE) to estimate parameters. However, MLE can be less reliable when the data is highly overdispersed or when the sample size is small, as it may lead to unstable results[6]. To solve these problems, the Bayesian approach offers a more flexible and informative solution. It uses prior information and combines it with observed data using Bayes' Theorem to produce a posterior distribution that better shows the uncertainty in the parameter estimates [7].

Unlike the frequentist approach, which only uses current data, the Bayesian approach combines data with prior knowledge to provide more reliable parameter estimates [8]. In frequentist estimation, multicollinearity can lead to unstable parameter estimates, with high variance and wide confidence intervals. This reduces the accuracy of the model and increases uncertainty in statistical inference. In contrast, the Bayesian approach can handle multicollinearity by incorporating appropriate priors, which help stabilize parameter estimates. The use of priors reduces the large variance of parameters and improves estimation accuracy, even when the data exhibits high multicollinearity [9].

This study focuses on the Generalized Poisson Regression (GPR) method to address overdispersion in count data. Previous studies have shown GPR to be effective, such as Sari's work on HIV cases in Riau Province, Aminullah's use of Bivariate GPR for infant and maternal mortality, and Chaniago's comparison of GPR and Negative Binomial Regression (NBR) for infant mortality in Probolinggo, with GPR performing better[10][11][12]. Alkema et al. applied a Bayesian approach combining multilevel regression and ARIMA for more accurate MMR estimation[13]. Meanwhile, Jakperik et al. analyzed maternal mortality in Ghana using Zero-Inflated Negative Binomial and Bayesian INLA, identifying age, marital status, and place of death as significant factors, and recommending improved health workforce distribution and facilities in rural areas[14].

Previous studies using Generalized Poisson Regression (GPR) still estimated parameters with the Maximum Likelihood Estimation (MLE) method, which has the drawback of potential bias when the sample size is small. Therefore, this study employs an alternative approach, namely Bayesian Generalized Poisson Regression (BGPR), which can accommodate overdispersion in the data[15]. The application of BGPR in health data analysis has been widely used to improve the accuracy of parameter estimation and enhance understanding of risk factors. This study aims to identify the significant factors affecting maternal mortality in NTT Province using the Bayesian Generalized Poisson Regression approach. The data used are secondary data obtained from the Central Statistics Agency (BPS) and the NTT Provincial Health Office for the year 2024. By applying BGPR, this study is expected to produce an optimal model that more accurately, stably, and comprehensively describes the relationship between predictor variables and maternal mortality.

2. **Methods**

2.1. Dataset

The data used in this study comprise 27 regencies and cities in NTT Province for 2024, as published by Statistics Indonesia (BPS) in 2024. The data is secondary data obtained from the 2024 NTT Provincial Health Profile [16]. This study uses districts/cities in NTT Province as the unit of analysis. The response variable in this study is the number of maternal deaths (Y), while the predictor variables include: percentage of K4 antenatal care visits (X1), percentage of blood pressure examinations (Td+) (X2), percentage of iron tablet supplementation coverage (TTD) (X3), percentage of active family planning participants (X4), number of complications treated by midwives (X5), and percentage of women who were married under the age of 17 (X6).

2.2. Overdispersion

Overdispersion occurs when the variance of count data is greater than its expected value, thereby violating the equidispersion assumption of Poisson regression[17]. If ignored, this can lead to inefficient estimates and invalid significance tests. Overdispersion can be detected by comparing the deviance or Pearson chi-square to the degrees of freedom; a ratio greater than 1 indicates the presence of overdispersion [18].

$$\phi = \frac{\chi_p^2}{n - p - 1} \tag{1}$$

$$\chi_p^2 = \sum_{i=1}^{n} \frac{(y_i - \hat{\mu}_i)^2}{\text{var}(\hat{\mu}_i)} \tag{2}$$

2.3. Posterior Distribution

The posterior distribution is the core of Bayesian inference, obtained through Bayes' Theorem as follows:

$$p(\theta|y) = \frac{p(y|\theta)p(\theta)}{p(y)} \tag{3}$$

where $p(\theta|y)$ is the posterior distribution, $p(y|\theta)$ is the likelihood, $p(\theta)$ is the prior, and $p(y)$ is the evidence (marginal likelihood). For the Generalized Poisson Regression model, the explicit form of the posterior distribution is generally not analytically available due to the complexity of the likelihood function. Therefore, posterior parameter estimation is carried out numerically using sampling methods such as Markov Chain Monte Carlo (MCMC) [7], particularly Metropolis-Hastings or Gibbs sampling [19].

2.4. Bayesian information criterion (BIC)

Bayesian Information Criterion (BIC) is one of the tools used to compare statistical models and is commonly employed in model selection, including within the Bayesian approach[20]. BIC can be defined as:

$$BIC = -2 \log L(\hat{\theta}) + k \log n \tag{4}$$

where $L(\hat{\theta})$ is the maximum value of the model's likelihood function, k s the number of parameters in the model, and n is the number of data points. Although BIC originates from the frequentist approach, it is still widely used due to its ease of implementation and its ability to provide an asymptotic approximation to model evidence or marginal likelihood [21].

2.5. Flow System Diagram

The system flow diagram is a visual representation that illustrates the sequence or workflow of a program. The system to be developed aims to model the number of maternal deaths in NTT Province using the Bayesian Generalized Poisson Regression approach.

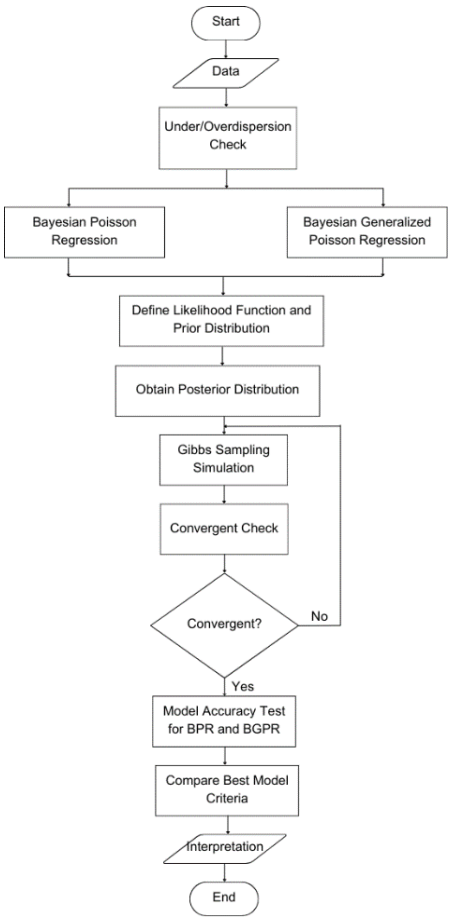

Figure 1. Flowchart

3. Results and Discussion

This chapter lays out specific instructions for writing the full text, including the article section, the systematic chapter and its contents. These specific instructions will guide the entire editorial process of the article as shown in Figure 2.

3.1. Overdispersion

The overdispersion is greater than 1, indicating that the data is overdispersion in the Poisson regression model. This was assessed by calculating Pearson's chi-squared value divided by the degrees of freedom [22]. The result, 12.31, is greater than 1, confirming that the data exhibit overdispersion in the Poisson regression model.

3.2. Bayesian Poisson Regression

In classical Poisson regression, the count data y_i is modeled as [23]:

$$y_i \sim Poisson(\lambda_i)$$
$$\lambda_i = \exp(x_i^T \beta) \quad (5)$$

Before estimating the parameters in Bayesian Poisson Regression, the first step is to determine the posterior distribution. The posterior distribution is obtained by applying Bayes' Theorem, which combines information from the likelihood and the prior distribution.

$$L(\beta) = \prod_{i=1}^{n} \frac{e^{-\lambda_i} \lambda_i^y}{y!}$$

$$L(\beta) = \prod_{i=1}^{n} \frac{e^{-exp(x_i^T \beta)} . exp\left(x_i^T \beta\right)^y}{y!} \tag{6}$$

$$f(\beta|y) = \frac{\beta^\alpha}{\Gamma(\alpha)} \theta^{\alpha-1} e^{-\beta\theta} \tag{7}$$

Thus, the posterior distribution is obtained as follows:

$$f(\beta|y) \propto \frac{\beta^\alpha}{\Gamma(\alpha)} \theta^{\alpha-1} e^{-\beta\theta} \times \prod_{i=1}^{n} \frac{e^{-exp(x_i^T \beta)} . exp\left(x_i^T \beta\right)^y}{y!} \tag{8}$$

The posterior distribution above is difficult to compute analytically; therefore, the Gibbs Sampling method is used as a solution. In Bayesian Poisson regression, a Gamma distribution is used as the prior because it is the conjugate prior of the Poisson distribution. The first step to ensure reliable parameter estimation is to examine the trace plot and the Monte Carlo (MC) Error value [24]. A stable trace plot with no clear pattern indicates that the sampling process has converged. Meanwhile, a small MC Error (less than 5% of the standard deviation) suggests that the parameter estimates are accurate [25]. Subsequently, parameter estimates are derived from the credible interval, which provides a range of values with a high level of confidence [26].

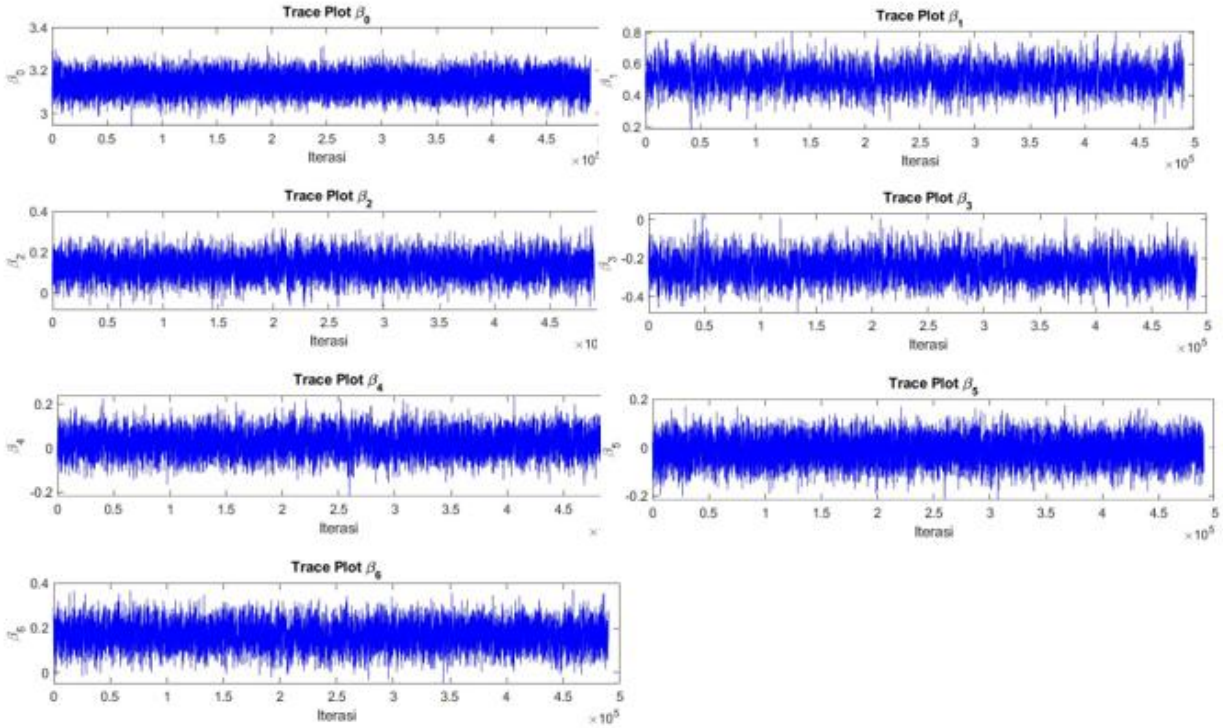

Figure 2. Trace Plots of the Estimated Beta Parameters in Bayesian Poisson Regression

From Figure 1, it can be observed that the beta values from β_0 to β_6 exhibit stability or stationarity. This is evident from the trace plots, which fluctuate randomly around the mean without any discernible trend. Such behaviour indicates that the parameter estimation process has reached convergence, meaning the results are reliable for further analysis. The stable trace plots also suggest that the sampling algorithm has effectively explored the parameter space and provided representative estimates of the posterior distribution [27].

Table 1. MC Error Bayesian Poisson Regression

Parameter	Standard Deviation	5% Standard Deviation	MC Error	Comment
$\boldsymbol{\beta_0}$	0.0411	0.0021	0.0001	convergence
$\boldsymbol{\beta_1}$	0.0709	0.0035	0.0027	convergence
$\boldsymbol{\beta_2}$	0.0495	0.0025	0.0017	convergence
$\boldsymbol{\beta_3}$	0.0595	0.0030	0.0012	convergence
$\boldsymbol{\beta_4}$	0.0484	0.0024	0.0021	convergence
$\boldsymbol{\beta_5}$	0.0469	0.0023	0.0018	convergence
$\boldsymbol{\beta_6}$	0.0499	0.0025	0.0003	convergence

From Table 1, it can be concluded that the MC Error (Monte Carlo Error), which is less than 5% of the standard deviation, shows that the model's estimates are quite accurate. A low MC Error means the uncertainty in the estimates is small compared to the standard deviation, indicating stable and reliable results. This also suggests that the simulation or estimation process has reached convergence, meaning the algorithm has stabilized and the parameter values no longer change significantly, even with more iterations. This stability ensures that the results are trustworthy and not fluctuating too much. Therefore, the estimates can be considered reliable.

Table 2. Bayesian Poisson Regression Estimation Parameter

Parameter	Parameter Estimator	2.5% Percentile	97.5% Percentile	Comment
$\boldsymbol{\beta_0}$	3.1412	3.0595	3.2204	Significant
$\boldsymbol{\beta_1}$	0.5157	0.3757	0.6550	Significant
$\boldsymbol{\beta_2}$	0.1318	0.0342	0.2296	Significant
$\boldsymbol{\beta_3}$	-0.2487	-0.3625	-0.1282	Significant
$\boldsymbol{\beta_4}$	0.0243	-0.0697	0.1193	Not Significant
$\boldsymbol{\beta_5}$	-0.0113	-0.1054	0.0789	Not Significant
$\boldsymbol{\beta_6}$	0.1672	0.0693	0.2641	Significant

Based on Table 2, the significant variables in the model are X1, X2, X3, and X6. This determination is made by examining each variable's credible interval (CI). If the CI does not include zero, the variable is considered to have a significant effect on the model [26]. In this case, the CI for X1, X2, X3, and X6 do not include zero, indicating that these four variables have a statistically significant influence. On the other hand, variables whose CI include zero are considered not significant, as there is insufficient evidence to suggest a meaningful effect in the model.

3.3. Bayesian Generalized Poisson Regression

In the Generalized Poisson Regression model, the conditional probability function of y_i given the predictors $x_{1i}, x_{2i}, \dots, x_{pi}$ is defined as follows [28].

$$P(y, \mu, \theta) = \left(\frac{\mu}{1+\theta\mu}\right)^y \frac{(1+\theta\mu)^{y-1}}{y!} exp\left(-\frac{\mu(1+\theta\mu)}{1+\theta\mu}\right) \tag{9}$$

Based on Equation (5), the likelihood function is derived and presented in Equation (6). The prior specification in the Generalized Poisson Regression model assumes that the regression parameters β follow a Gamma distribution, while the dispersion parameter θ is assumed to follow a Normal distribution.

$$L(\beta, \theta) = \prod_{i=1}^{n} \left(\frac{e^{x_i^T\beta}}{1+\theta e^{x_i^T\beta}}\right) \frac{(1+\theta y)^{y-1}}{y!} exp\left(\frac{e^{x_i^T\beta}(1+\theta y)}{1+\theta e^{x_i^T\beta}}\right) \tag{10}$$

$$f(\theta|y) = \frac{\beta^\alpha}{\Gamma(\alpha)} \theta^{\alpha-1} e^{-\beta\theta} \tag{11}$$

$$f(\beta|y) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\left(\frac{\beta-\mu_\beta}{2\sigma^2}\right)} \tag{12}$$

The resulting posterior distribution is as follows:

$$f(\beta,\theta|y) \propto \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\left(\frac{\beta-\mu_\beta}{2\sigma^2}\right)} \times \frac{\beta^\alpha}{\Gamma(\alpha)} \theta^{\alpha-1} e^{-\beta\theta} \times \prod_{i=1}^{n} \left(\frac{e^{x_i^T\beta}}{1+\theta e^{x_i^T\beta}}\right) \frac{(1+\theta y)^{y-1}}{y!} exp\left(\frac{e^{x_i^T\beta}(1+\theta y)}{1+\theta e^{x_i^T\beta}}\right) \tag{13}$$

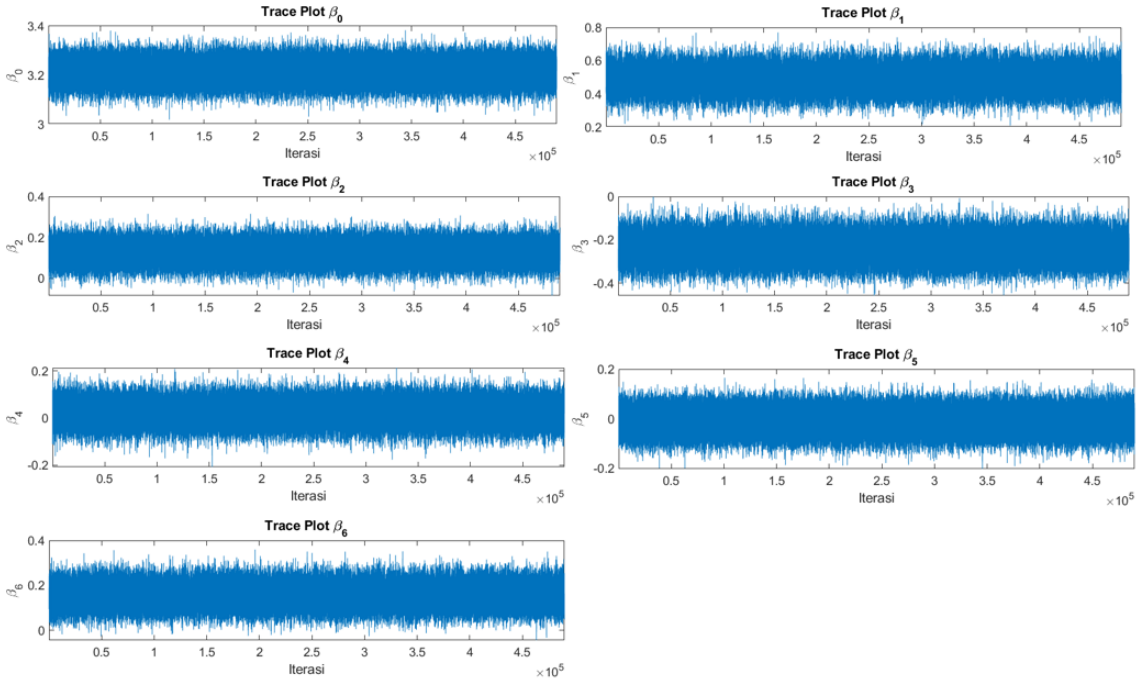

Figure 3. Trace Plots of Beta Parameter Estimates in Bayesian Generalized Poisson Regression

Figure 3 shows the trace plot generated from simulations using the Gibbs sampling algorithm, involving 500,000 iterations to obtain samples from the posterior distribution of the model parameters. This approach was taken because the posterior distribution is analytically intractable. Prior to sampling for analysis, a burn-in period of 10,000 iterations was conducted to ensure that the MCMC chain reached a stationary state. The resulting trace plots for the beta parameters exhibit stable and random patterns, indicating that the model has achieved good convergence.

Table 3. MC Error Bayesian Generalized Poisson Regression

Parameter	Standard Deviation	5% Standard Deviation	MC Error	Comment
$\boldsymbol{\beta_0}$	0.0405	0.002025	0.0011	convergence
$\boldsymbol{\beta_1}$	0.0653	0.003265	0.0019	convergence
$\boldsymbol{\beta_2}$	0.0454	0.00227	0.001	convergence
$\boldsymbol{\beta_3}$	0.0542	0.00271	0.0017	convergence
$\boldsymbol{\beta_4}$	0.0441	0.002205	0.0021	convergence
$\boldsymbol{\beta_5}$	0.0422	0.00211	0.0016	convergence
$\boldsymbol{\beta_6}$	0.0455	0.002275	0.0021	convergence

Based on Table 3, the MC Error value for the Bayesian Generalized Poisson model, which is less than 5% of the standard deviation, indicates that the beta parameters have reached convergence. This suggests that the sampling process using the MCMC method has stabilized, and the obtained parameter

estimates can be relied upon. In other words, the low MC Error value indicates that the variation in parameter estimates is minimal, making the model results consistent and accurate.

Table 4. Bayesian Generalized Poisson Regression Estimation Parameter

Parameter	Parameter Estimator	2.5% Percentile	97.5% Percentile	Comment
$\boldsymbol{\beta_0}$	3.2146	3.1342	3.2930	Significant
$\boldsymbol{\beta_1}$	-0.4873	0.3595	0.6154	Significant
$\boldsymbol{\beta_2}$	0.1252	0.0357	0.2137	Significant
$\boldsymbol{\beta_3}$	-0.2399	-0.3446	-1.1319	Significant
$\boldsymbol{\beta_4}$	-0.0234	-0.0640	-1.1091	Significant
$\boldsymbol{\beta_5}$	0.0092	-0.0925	-1.0724	Significant
$\boldsymbol{\beta_6}$	0.1564	0.0682	0.2468	Significant

Based on Table 4, which shows the credible intervals of the Bayesian Generalized Poisson Regression model, it can be concluded that all tested parameters show high significance values. This means that each parameter has a credible interval that does not include zero, indicating that these parameters have a significant influence on the observed variable.

3.4. Model Evaluation

The best model is determined using the BIC value of each model. The better model to use is the one with the smallest BIC value. Table 5 shows BIC values for every model.

Table 5. BIC Values

Model	BIC
Bayesian Poisson Regression	827.95
Bayesian Generalized Poisson Regression	400.40

Based on Table 7, the smallest BIC value for the Bayesian Generalized Poisson Regression model is 400.40. Therefore, it can be concluded that the best model in this study is the Bayesian Generalized Poisson Regression.

3.5. Interpretation

The parameter estimates for the Bayesian Generalized Poisson Regression model are as follows:

$$\hat{\mu} = \exp(3.2146 - 0.4873X_1 + 0.1252X_2 - 0.2399X_3 - 0.0234X_4 + 0.0092X_5 + 0.1564X_6)$$

Based on the parameter significance testing in the Bayesian Generalized Poisson Regression model, all parameters were found to be statistically significant. For the parameter β_1, which is estimated at -0.4873, it can be interpreted that for every 1% increase in the percentage of pregnant women who undergo at least four antenatal care visits (K4), assuming other variables remain constant, the average number of maternal deaths (Y) tends to decrease by a factor of μ_i = exp (0.4873) = 1.628, or approximately 2 fewer maternal deaths in NTT. This indicates that a higher number of antenatal visits (K4) is associated with a reduction in maternal mortality.

For the parameter β_2, which is estimated at 0.1252, it suggests that for every 1% increase in the percentage of pregnant women who receive complete Tetanus Toxoid (Td^+) immunization, assuming other variables remain constant, the average number of maternal deaths (Y) tends to increase by a factor of μ_i = exp (0.1252) = 1.133, or approximately 1 additional maternal death in NTT Province. This finding implies that an increase in Td^+ immunization coverage does not necessarily lead to a reduction in maternal mortality. While the immunization is crucial in preventing tetanus infection in mothers and infants, increasing its coverage alone may not be sufficient to reduce maternal death rates.

For β_3 = 0.2399, it can be said that for every 1% increase in the percentage of pregnant women receiving Iron and Folate supplementation (TTD), with other variables held constant, the average number of maternal deaths tends to increase by approximately **1** maternal death in NTT, as μ_i = exp (0.2399) ≈ 1.271. This suggests that, despite TTD's primary aim to prevent anemia in pregnant women and support healthy pregnancies, it may not be directly correlated with a decrease in maternal mortality.

For β_4 = 0.0234, it can be said that for every 1% increase in the percentage of pregnant women using active family planning (KB Aktif), with other variables held constant, the average number of maternal deaths tends to increase by approximately **1** maternal death in NTT, as $\mu_i = \exp(0.0234) \approx 1.024$. This indicates that an increase in the participation of active family planning among pregnant women is correlated with a rise in maternal mortality.

For β_5 = 0.0092, it can be said that for every 1% increase in the percentage of maternal complications handled by midwives, with other variables held constant, the average number of maternal deaths tends to increase by approximately **1** maternal death in NTT, as $\mu_i = \exp(0.0092) \approx 1.009$. This suggests that an increase in complications managed by midwives correlates with an increase in maternal mortality. This could indicate that complications during pregnancy or childbirth remain relatively high, and even though they are handled by healthcare providers such as midwives, delays in treatment, limited facilities, or the complexity of cases still pose a risk factor for maternal death.

For β_6= 0.1564, it can be said that for every 1% increase in the percentage of women married under the age of 17, with other variables held constant, the average number of maternal deaths tends to increase by approximately **1** maternal death in NTT, as $\mu_i = \exp(0.1564) \approx 1.169$. This indicates that the higher the number of women who marry at a young age (<17 years), the greater the risk of maternal mortality. This may be due to the higher risk of complications during pregnancy at a young age, both physically, mentally, and in terms of access to healthcare services. An underdeveloped body biologically and the lack of knowledge and readiness for pregnancy can increase the potential for maternal death.

3.6. Discussion

The results of this study indicate that the analysis was carried out comprehensively and systematically. The research process began with the development of a workflow (flowchart), the collection of maternal mortality data from official government sources, and the selection of an appropriate statistical algorithm to handle count data with overdispersion characteristics. In this case, the Bayesian Generalized Poisson Regression (BGPR) model was selected, as it is capable of accommodating variance greater than the mean thereby providing greater modeling flexibility compared to the classical Poisson regression model. The BGPR model uses a conjugate prior, and posterior parameter estimation is performed using the Markov Chain Monte Carlo (MCMC) simulation method, particularly the Gibbs Sampling algorithm. The study also compares the performance of the Bayesian Poisson Regression (BPR) and BGPR models using the Bayesian Information Criterion (BIC) to determine the most appropriate model. Furthermore, the use of credible intervals supports the identification of statistically significant predictor variables.

From a public health policy perspective, the findings offer valuable insights. The variables identified as significant through the credible intervals may reflect real health service gaps or socioeconomic factors contributing to maternal mortality. These can be used by regional health departments to prioritize interventions, such as increasing antenatal care coverage, addressing teenage marriage, or ensuring access to skilled birth attendants. Thus, the model not only serves an academic function but also provides evidence-based direction for maternal health policy formulation. Despite these contributions, the study has several limitations that warrant consideration. One limitation concerns the choice of prior distribution. While this study adopts a conjugate prior for computational simplicity, future research is encouraged to explore the use of uninformative or weakly informative priors to minimize subjectivity and better reflect real-world uncertainty.

Additionally, this study does not incorporate spatial dependencies between regions, which may be essential in understanding localized health disparities. Therefore, future studies could integrate spatial modeling techniques (e.g., Bayesian spatial regression or Geographically Weighted models) to capture regional variations and potentially improve model accuracy and policy relevance. Another potential source of bias could stem from the quality or completeness of the input data, which must be critically evaluated in future implementations

4. Conclusion

This study concludes that the Bayesian Generalized Poisson Regression (BGPR) model is effective in addressing overdispersion in maternal mortality data in East Nusa Tenggara Province. The model successfully identifies key factors associated with maternal mortality, such as antenatal care coverage (K4), complications handled by midwives, and early marriage rates. The parameter estimation using Markov Chain Monte Carlo (MCMC) with Gibbs Sampling demonstrates improved accuracy and flexibility compared to classical approaches.

The findings have important implications for maternal health policy, particularly in regions with similar challenges. Local governments can prioritize improving antenatal care quality, enhancing emergency obstetric services, and implementing community-based programs to reduce early marriage. Moreover, the Bayesian approach's ability to integrate prior information makes it especially suitable for data-limited or resource-constrained environments.

For future research, it is recommended to expand the spatial coverage and improve the quality of maternal health data, especially from remote areas. Using longitudinal data may also provide deeper insights into temporal trends and the effectiveness of health interventions. Additionally, incorporating spatial modeling approaches such as Bayesian Spatial Regression could help capture geographical disparities and guide more targeted policy decisions.

References

[1] World Health Organization, "Trends in maternal mortality 2000 to 2020," World Health Organization, 2023. [Online]. Available: https://www.who.int/publications/i/item/9789240068759

[2] Bappenas, "Roadmap Tujuan Pembangunan Berkelanjutan (SDGs) Indonesia 2020–2030," Bappenas, Jakarta, 2022. [Online]. Available: https://sdgs.bappenas.go.id/website/wp-content/uploads/2021/02/Roadmap_Bahasa-Indonesia_File-Upload.pdf

[3] Kementerian Kesehatan RI, "Profil Kesehatan Indonesia Tahun 2022," Kementerian Kesehatan RI, Jakarta, 2023. [Online]. Available: https://kemkes.go.id/id/profil-kesehatan-indonesia-2022

[4] Ö. İŞçi Güneri and B. Durmuş, "Models for Overdispersion Count Data with Generalized Distribution: An Application to Parasites Intensity," *J. New Theory*, no. 35, pp. 48–61, Jun. 2021, doi: 10.53570/jnt.902066.

[5] F. Famoye and K. P. Singh, "Zero-Inflated Generalized Poisson Regression Model with an Application to Domestic Violence Data," *J. Data Sci.*, vol. 4, no. 1, pp. 117–130, Jul. 2021, doi: 10.6339/JDS.2006.04(1).257.

[6] H. Zamani, P. Faroughi, and N. Ismail, "Bivariate generalized Poisson regression model: applications on health care data," *Empir. Econ.*, vol. 51, no. 4, pp. 1607–1621, Dec. 2016, doi: 10.1007/s00181-015-1051-7.

[7] A. Gelman, J. B. Carlin, H. S. Stern, D. B. Dunson, A. Vehtari, and D. B. Rubin, "Bayesian Data Analysis Third edition (with errors fixed as of 20 February 2025)".

[8] R. Van De Schoot, S. D. Winter, O. Ryan, M. Zondervan-Zwijnenburg, and S. Depaoli, "A systematic review of Bayesian articles in psychology: The last 25 years.," *Psychol. Methods*, vol. 22, no. 2, pp. 217–239, Jun. 2017, doi: 10.1037/met0000100.

[9] A. G. Assaf and M. Tsionas, "A Bayesian solution to multicollinearity through unobserved common factors," *Tour. Manag.*, vol. 84, p. 104277, Jun. 2021, doi: 10.1016/j.tourman.2020.104277.

[10] A. D. Chaniago and S. P. Wulandari, "Pemodelan Generalized Poisson Regression (GPR) dan Negative Binomial Regression (NBR) untuk Mengatasi Overdispersi pada Jumlah Kematian Bayi di Kabupaten Probolinggo," *J. Sains Dan Seni ITS*, vol. 11, no. 6, pp. D448–D455, May 2023, doi: 10.12962/j23373520.v11i6.93240.

[11] A. A. H. Aminullah and P. Purhadi, "Pemodelan untuk Jumlah Kasus Kematian Bayi dan Ibu di Jawa Timur Menggunakan Bivariate Generalized Poisson Regression," *J. Sains Dan Seni ITS*, vol. 8, no. 2, pp. D72–D78, Jan. 2020, doi: 10.12962/j23373520.v8i2.44693.
[12] N. Sari, "Solusi Overdispersi Menggunakan Generalized Poisson Regression (Studi Kasus : Penderita HIV di Provinsi Riau)," vol. 4, no. 2, 2018.
[13] L. Alkema *et al.*, "A Bayesian approach to the global estimation of maternal mortality," *Ann. Appl. Stat.*, vol. 11, no. 3, Sep. 2017, doi: 10.1214/16-AOAS1014.
[14] D. Jakperik, S. Nadarajah, and M. J. Adjabui, "Bayesian Additive Modeling of Maternal Mortality In Ghana," Dec. 08, 2021, *In Review*. doi: 10.21203/rs.3.rs-1089149/v1.
[15] J.-F. Angers and A. Biswas, "A Bayesian analysis of zero-in&ated generalized Poisson model".
[16] Dinas Kesehatan Provinsi Jawa Barat, "Profil Kesehatan Provinsi Jawa Barat Tahun 2024," Dinas Kesehatan Provinsi Jawa Barat, Bandung, 2024. Accessed: Jan. 21, 2025. [Online]. Available: https://app-diskes.jabarprov.go.id/drive/s/zAjp8Ac58gKWBp3
[17] F. Suryadi, S. Jonathan, K. Jonatan, and M. Ohyver, "Handling overdispersion in poisson regression using negative binomial regression for poverty case in NTT," *Procedia Comput. Sci.*, vol. 216, pp. 517–523, 2023, doi: 10.1016/j.procs.2022.12.164.
[18] Y. Tiara, M. N. Aidi, E. Erfiani, and R. Rachmawati, "Overdispersion Handling In Poisson Regression Model By Applying Negative Binomial Regression," *BAREKENG J. Ilmu Mat. Dan Terap.*, vol. 17, no. 1, pp. 0417–0426, Apr. 2023, doi: 10.30598/barekengvol17iss1pp0417-0426.
[19] M. A. Mukid and A. Rusgiyono, "Simulasi Stokastik Menggunakan Algoritma Gibbs Sampling".
[20] A. Chakrabarti and J. K. Ghosh, "AIC, BIC and Recent Advances in Model Selection," in *Philosophy of Statistics*, Elsevier, 2011, pp. 583–605. doi: 10.1016/B978-0-444-51862-0.50018-6.
[21] J. Hu, H. Qin, T. Yan, and Y. Zhao, "Corrected Bayesian Information Criterion for Stochastic Block Models," *J. Am. Stat. Assoc.*, vol. 115, no. 532, pp. 1771–1783, Oct. 2020, doi: 10.1080/01621459.2019.1637744.
[22] L. P. Rahayu, K. Sadik, and I. Indahwati, "Overdispersion study of poisson and zero-inflated poisson regression for some characteristics of the data on lamda, n, p," *Int. J. Adv. Intell. Inform.*, vol. 2, no. 3, p. 140, Nov. 2016, doi: 10.26555/ijain.v2i3.73.
[23] Z. A. Budiawan and Y. Widyaningsih, "Poisson Regression Models To Analyze Factors That Influence The Number Of Tuberculosis Cases In Java," *BAREKENG J. Ilmu Mat. Dan Terap.*, vol. 17, no. 3, pp. 1761–1772, Sep. 2023, doi: 10.30598/barekengvol17iss3pp1761-1772.
[24] A. M. H. Van Der Veen, "Bayesian methods for type A evaluation of standard uncertainty," *Metrologia*, vol. 55, no. 5, pp. 670–684, Oct. 2018, doi: 10.1088/1681-7575/aad103.
[25] D. K. Sari, N. W. S. Wardhani, and S. Astutik, "Parameter Estimation of Structural Equation Modeling Using Bayesian Approach," *CAUCHY J. Mat. Murni Dan Apl.*, vol. 4, no. 2, pp. 86–94, May 2016, doi: 10.18860/ca.v4i2.3492.
[26] A. Joshi, T. Ollila, I. Immonen, and S. Kulathinal, "Bayesian Simultaneous Credible Intervals for Effect Measures from Multiple Markers," *Stat. Biopharm. Res.*, vol. 15, no. 3, pp. 638–653, Jul. 2023, doi: 10.1080/19466315.2022.2110935.
[27] A. B. Lawson, *Bayesian Disease Mapping: Hierarchical Modeling in Spatial Epidemiology, Third Edition*, 3rd ed. Chapman and Hall/CRC, 2018.
[28] P. C. Consul and G. C. Jain, "A Generalization of the Poisson Distribution," *Technometrics*, vol. 15, no. 4, pp. 791–799, Nov. 1973, doi: 10.1080/00401706.1973.10489112.