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STATMAT (Jurnal Statistika dan Matematika)
P-ISSN: 2655-3724 E-ISSN: 2720-9881
Vol. 8, No. 2, August 2026
5th article, Pages: 246 – 257
DOI: https://doi.org/10.32493/sm.v8i2.55544

Application of The Generalized Linear Model With Negative Binomial Distribution on Birth Rates in West Java 2023

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ABSTRACT

The uneven decline in birth rates in West Java Province requires the identification of specific determinants of birth rates at the local level. This study aims to analyze the relationship between factors affecting birth rates, including the percentage of couples of childbearing age (PUS) using family planning (KB), Gross Regional Domestic Product (GRDP) growth rate, percentage of working women, gender empowerment index, percentage of marital status, percentage of college graduates, and percentage of first marriages between the ages of 25 and 30. Factor analysis uses the Generalized Linear Model (GLM) and Integrated Nested Laplace Approximation (INLA) models with Poisson and negative binomial distributions. Both distributions are used and compared with AIC, BIC, and DIC evaluations. The evaluation results prove that the negative binomial distribution is the best model for modeling birth data. The main findings show that the percentage of women working consistently has a negative effect on both the GLM and INLA models. Another finding is that there is a negative relationship between the variables of contraceptive use in PUS and the age of marriage between 25 and 30 years in the GLM model, but there is no significant evidence in the INLA approach.
Keywords: Birth Rate, Negative Binomial, GLM, INLA

ARTICLE INFO	
Submission received: 09 December 2025	Accepted: 31 August 2026
Revised: 19 August 2026	Published: 31 August 2026
Available on: https://doi.org/10.32493/sm.v8i2.55444	

INTRODUCTION

Indonesia ranks fourth as the country with the largest population in the world. As a developing country, Indonesia faces major challenges in curbing population growth. One of the main components that determine the rate of population growth is the birth rate. A high birth rate can increase the demographic burden, increase poverty, reduce quality of life, and put pressure on the availability of natural resources and public infrastructure. One of the main indicators is the birth rate or Total Fertility Rate (TFR). According to the World Bank in 2023, Indonesia's TFR has declined significantly since 1960, from 5.5 children per woman to 2.127 children per woman in 2023. Although this figure has decreased significantly, the 2020-2024 National Medium-Term Development Plan (RPJMN) targets a reduction in the TFR to 2.1 children per woman by 2024.

Although nationally the birth rate shows a downward trend, this decline has not been uniform across all regions. This situation is consistent with West Java Province, which shows disparities in birth rates across different regions. Although West Java's TFR is below the threshold expected by the government, this achievement is not uniform across all regions. This shows that birth control is not sufficient through national policies but needs to be

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adapted to the specific conditions of each region. Differences in birth rates between regions indicate the existence of determining factors that influence them (1). Based on previous research, birth rates increase as a result of early marriage and limited economic status (2,3). On the other hand, higher education has the potential to reduce birth rates because it can influence mindsets in determining the age of marriage (4). Another factor is that the level of women's participation in the workforce has the potential to reduce births (5). The decline in birth rates is also influenced by increasing attitudes of gender equality in society. Egalitarian attitudes towards gender have led to increased participation of women in the workforce, which has become a driver for delaying the decision to marry and have children (6,7).

Proper statistical analysis in modeling data is necessary to understand birth distributions. Classical linear models only assume a normal distribution, which is often insufficient for data that are distributed other than normally, such as Poisson, binomial, gamma, and others. Therefore, other alternatives are used to model data, such as the Generalized Linear Model (GLM), which provides flexibility in modeling data using link functions (8,9). GLM allows for better handling of non-linear relationships in heterogeneous data compared to ordinary linear models (10). GLM applications are commonly found in social and demographic research. In the context of birth rate analysis, GLM is able to accommodate event data using Poisson or negative binomial distributions to overcome overdispersion. Meanwhile, Integrated Nested Laplace Approximation (INLA) is a statistical approach used to estimate complex hierarchical or Bayesian models (11). Unlike Markov Chain Monte Carlo (MCMC), which is sampling-based and time-consuming, INLA uses a deterministic approach based on Laplace approximation to estimate the posterior distribution of model parameters (12). INLA can be used when the model involves complex dependency structures and requires efficient Bayesian inference.

This study aims to identify demographic and non-demographic variables that significantly influence birth patterns in West Java province. This study is not only descriptive but also uses statistical analysis that can provide empirical evidence through model estimation results. This analysis helps identify areas in West Java with high birth rates and plan targeted strategies to manage population growth and minimize birth disparities between regions.

MATERIAL AND METHODS

This study used quantitative methods with RStudio software. The research was conducted in several stages, as shown in Figure 1.

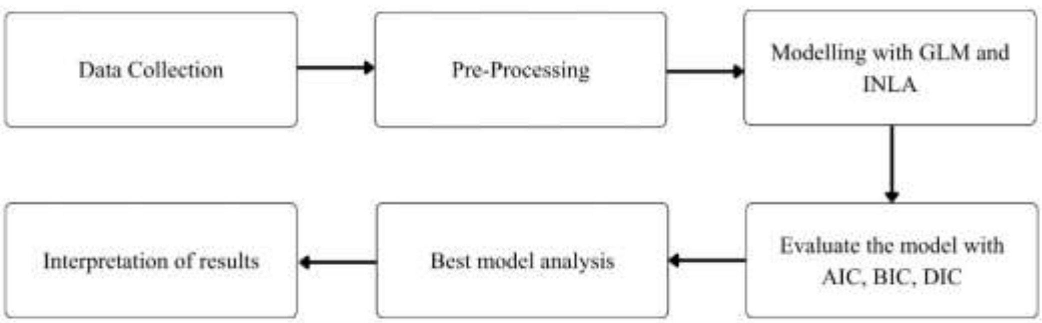

Figure 1. Research Framework

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Data Collection

The data used is secondary data obtained from several sources. Data was collected from 27 districts/cities in West Java Province, using the number of births as the response variable and seven explanatory variables. The variables taken are a combination of demographic and non-demographic factors. The research variables can be seen in Table 1.

Table 1. Variable Description

Variable	Definition	Source
Y	Birth Rate	BPS
X_1	Percentage of couples of childbearing age using contraception	BKKBN
X_2	GRDP Growth Rate	BPS
X_3	Percentage of Women in Employment	BPS
X_4	Gender Empowerment Index	BPS
X_5	Percentage of Youths Based on Marital Status	OpenData Jabar
X_6	Percentage of Youth with College Degrees	BPS
X_7	Percentage of First Marriage Age 25-30 years	BPS

Pre-Processing

The collected data is checked for completeness and consistency. This process includes handling missing data, checking outliers, and standardizing formats to obtain values with uniform intervals. Multicollinearity testing was also conducted using VIF. A VIF value above 10 is considered high and indicates high multicollinearity (13). Multicollinearity occurs when the correlation of predictor variables is greater than 0.8 or less than -0.8 (14)

Generalized Linear Model (GLM)

The Generalized Linear Model (GLM) is a statistical approach introduced by Nelder and Wedderburn in 1972 (15). GLM extends ordinary linear regression by using a model that allows the relationship between response variables through a link function (9,16). This model allows response variables to be described with error distributions other than normal. GLM provides a modeling framework for commonly used statistical models. The model is defined in a set of observations $y_1, \ldots, y_n$ which are the results of random variables $Y_1 \ldots, Y_n$ (17). GLM has the following equation:

$$\theta_i = \beta_0 + \beta_1 x_{i1} + \cdots + \beta_p x_{ip} + \epsilon_i \tag{1}$$

with
θ_i : linear predictor for the i-th observation
$\beta = \beta_0, \beta_1, \ldots, \beta_p$: regression coefficient
$x_i = 1, x_{1i}, \ldots, x_{ip}$: predictor value
$\epsilon_i \sim N(0, \sigma^2)$: error value with an expectation of 0 and constant variance

With response variables $\mu_i = E(Y_i)$ and the linear predictor value is bound to the link function:

$$g(\mu_i) = \theta_i \tag{2}$$

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The link function can be adjusted to the data distribution used. Since the response variable is used in the form of a number, the appropriate distributions are the Poisson and negative binomial distributions.

Poisson Distribution

The Poisson distribution is widely used in discrete data analysis. In the Poisson distribution, it is assumed that the response variable represents the number of events (18). Poisson models the probability of an event occurring in a certain time interval (19). The link function of the Poisson distribution is simply the natural logarithm of the expected value of the response variable.

$$\ln \lambda_i = \beta_0 + \beta_1 x_{i1} + \cdots + \beta_p x_{ip}, \quad \lambda = e^{\beta_0 + \beta_1 x_{i1} + \cdots + \beta_p x_{ip}} \tag{3}$$

The Poisson distribution assumes that the expected value and variance of the response variable are equal.

$$E(Y) = V(Y) = \lambda \tag{4}$$

In real cases, data that does not meet these assumptions is often encountered. This occurs when the data is overdispersed, where the variance of the data is greater than the expected value (20).

Negative Binomial Distribution

The negative binomial distribution is typically used for count data. The negative binomial distribution is necessary to address conditions of overdispersion that cannot be handled by the Poisson distribution (21). The limitations of the Poisson distribution can result in standard error estimates that are too small. This condition is consistent with birth data, which shows considerable overdispersion. The probability function of the negative binomial distribution is as follows:

$$P(Y_i = y; \alpha, \mu_i) = \frac{\Gamma(y+\alpha)}{\Gamma(\alpha) y!} \left(\frac{\alpha}{\mu_i + \alpha}\right)^{\alpha} \left(\frac{\mu_i}{\mu_i + \alpha}\right)^{y} \tag{5}$$

For $y \in \{0, 1, 2, \ldots\}$ with mean μ_i and variance:

$$Var(Y_i) = \frac{\mu_i + \mu_i^2}{\alpha} \tag{6}$$

The logarithmic link function is used in negative binomial regression. The model is written as follows:

$$\begin{cases} Y_i \sim NB(\alpha, \mu_i), \\ log(\mu_i) = \beta_0 + \beta_1 x_{i1} + \cdots + \beta_p x_{ip} \end{cases} \tag{7}$$

Inregrated Nested Laplace Approximation (INLA)

Integrated Nested Laplace Approximation (INLA) is a method developed from the MCMC method that is capable of producing more accurate estimates and faster computations

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(22). As the name suggests, this method uses the Laplace approach (23). Bayesian estimation combined with INLA provides a robust and efficient statistical framework for interpreting complex models (24). INLA can integrate modeling approaches such as GLM models and uncertainty analysis into a more general hierarchical framework (25). The INLA approach based on Bayes' theorem is useful for finding the marginal posterior distribution for each element of the parameter vector (23). This approach has three main components, namely the prior distribution that explains the initial assumptions about the parameters before the data is collected, the likelihood function that shows the probability of the observed data based on certain parameter values, and the posterior distribution which is the confidence of each parameter after taking into account the existing data (26). Bayes' theorem can be written in the following equation:

$$\pi(x_i|y) = \int \pi(x_i|\theta, y)\pi(\theta|y)d\theta\,, \quad \pi(\theta_k|y) = \int \pi(\theta|y)d\theta_{-k} \tag{8}$$

INLA consists of three steps introduced by Rue et al. (2009). The first step is to approximate the posterior marginals θ with $\pi(\theta|y)$ using Gaussian and Laplace approximations. The second step involves calculating a simplified Laplace approximation for $\pi(x_i|\theta, y)$. The third step combines the first and second steps using numerical integration. These iterative Laplace calculations can produce accurate estimates in less time than MCMC.

Best Model Evaluation

The best model evaluation is used to assess the extent to which the constructed model is able to describe the relationship between variables well without causing overfitting. The evaluation is carried out using three main criteria, namely AIC, BIC, and DIC. In general, smaller AIC, BIC, and DIC values indicate a better model, as they signify an optimal balance between the level of model suitability and model complexity (27,28).

a. Akaike Information Criterion (AIC)

AIC tends to choose more complex models (overfitting), especially with small samples, but is efficient for prediction (29).

$$AIC = -2\ln \mathcal{L}(\theta_{mle}|y) + 2k \tag{9}$$

Where $\mathcal{L}(\theta_{mle}|y)$ maximum likelihood parameter value of θ_{mle} based on y. $2k$ is a function of the number of free parameters of model k reflecting the parametric complexity of the model. In AIC, complexity is considered independent (28).

b. Bayesian Information Criterion (BIC)

BIC is more consistent in selecting the correct model if the model actually exists among the candidates, and is stricter in complexity penalties, so it tends to select simpler models (29).

$$BIC = -2\ln \mathcal{L}(\theta_{mle}|y) + k\ln(n) \tag{10}$$

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BIC employs a method that is comparable to AIC, except with BIC, the model's complexity is dependent on the dataset's sample size (n). This indicates that with a bigger sample size, BIC requires each additional parameter to explain a greater percentage of the dataset (28).

c. Deviance Information Criterion (DIC)

Introduced by Spiegelharter et al. in 2002, DIC is a generalization of the AIC and BIC hierarchical models that are used as comparison criteria for complicated hierarchical models (25). Defined as follows:

$$DIC = \overline{D} + p_D \tag{11}$$

Where $\overline{D}$ is the posterior mean of deviance of the model and p_D is the effective number of parameters in the model (25).

RESULTS AND DISCUSSION

Multicollinearity Test

The multicollinearity test for the seven predictor variables was conducted based on the VIF value. The test results can be seen in Table 2. The results show that the VIF values are relatively low and below 10, so there is no evidence of multicollinearity between the predictor variables.

Table 2. VIF Values of Predictor Variables

Variable	VIF	Correlation
X_1	2.035	-0.288
X_2	1.194	-0.0418
X_3	1.368	-0.318
X_4	1.156	-0.2809
X_5	4.119	-0.1384
X_6	4.527	0.1238
X_7	3.376	-0.1638

Table 2 shows that the correlation values of the predictor variables with Y are relatively small. The variable correlations are below the threshold. These analysis results reinforce the findings from the previous VIF values. Thus, all predictor variables can be used in the regression model without variable deletion or transformation.

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GLM and INLA Model Analysis

a. Poisson Distribution

Table 3. Poisson Distribution Results

Coefficient	GLM		INLA	
	Estimate	*p-value*	Mean	Interval
(Intercept)	-1.291	2×10^{-16} ***	-1.291	(-1.454, -1.129)
X_1	-0.018	2×10^{-16} ***	-0.018	(-0.019, -0.018)
X_2	-0.056	2×10^{-16} ***	-0.056	(-0.059, -0.053)
X_3	-0.011	2×10^{-16} ***	-0.011	(-0.012, -0.009)
X_4	-0.002	2×10^{-16} ***	0.002	(-0.002, -0.002)
X_5	-0.004	2×10^{-16} ***	-0.004	(-0.004, -0.003)
X_6	-0.002	9.53×10^{-7} ***	-0.002	(-0.003, -0.001)
X_7	-0.008	2×10^{-16} ***	-0.008	(-0.009, -0.007)

Based on the results of the GLM model with Poisson distribution, the predictor variables of the percentage of couples of childbearing age using contraception, the GRDP growth rate, the percentage of working women, gender empowerment index, percentage of youth with marital status, percentage of youth with college degrees, and percentage of first marriages between the ages of 25 and 30 showed a significant effect on the number of births with a p-value < 0.001. All variables showed a negative effect on the number of births. The INLA model results are in line with the GLM model results, which show that the predictor variables of the percentage of couples of childbearing age using contraception, the GRDP growth rate, the percentage of women in the workforce, the gender empowerment index, the percentage of young people who are married, the percentage of young people who have completed college, and the percentage of people who marry for the first time between the ages of 25 and 30 have a significant effect. This is indicated by the confidence interval not containing zero. With a 95% confidence interval, the variables percentage of PUS using contraception, GRDP growth rate, percentage of women working, gender empowerment index, percentage with marital status, percentage with college education, and percentage of first marriage age 25-30 years have a negative effect on the number of births.

b. Negative Binomial Distribution

Table 4. Negative Binomial Distribution Results

Coefficient	GLM		INLA	
	Estimate	*p-value*	Mean	Interval
(Intercept)	36.22	3.6×10^{-7} ***	36.020	(17.977, 54.022)
X_1	-0.05	0.049 *	-0.051	(-0.106, 0.004)
X_2	-0.033	0.813	-0.018	(-0.319, 0.286)
X_3	-0.221	0.003 **	-0.219	(-0.409, -0.028)
X_4	-0.015	0.449	-0.016	(-0.064, 0.031)
X_5	0.008	0.788	0.010	(-0.065, 0.085)
X_6	0.025	0.594	0.020	(-0.089, 0.128)
X_7	-0.078	0.027 *	-0.072	(-0.166, 0.022)

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The results of the model using the GLM approach show a significant effect on the predictor variables of contraceptive use percentage in PUS, percentage of working women, and percentage of women married between the ages of 25 and 30. The significance level can be seen from the p-value, which is below the significance level of 0.05, with p-values of 0.049, 0.003, and 0.027, respectively. With a 95% confidence interval, a 5% increase in the percentage of PUS using contraception can reduce births by 0.05 on a logarithmic scale or 0.049 on the original scale. With a 99% confidence interval, every 1% increase in the percentage of working women has a negative impact of 0.221 on a logarithmic scale or 0.198 on the original scale. Each 5% increase in the percentage of young people married between the ages of 25 and 30 can reduce the birth rate by 0.078 on a logarithmic scale or 0.075 on a natural scale. This is assuming that other predictors remain constant. Meanwhile, other predictor variables have no significant effect because the p-value is > 0.05. The results obtained from the INLA approach show differences from the GLM model. From the INLA results, the percentage of women working variable has a significant effect of -0.219 on a logarithmic scale with a 95% confidence interval (0.409, -0.028). Every 1% increase in the percentage of women working can reduce births by 0.219 on a logarithmic scale or 0.197 on a native scale. Meanwhile, there was no empirical evidence found to indicate a significant influence of the variables of the percentage of PUS using family planning and the percentage of those aged 25-30 years old. Other variables did not show a significant influence.

Best Model Analysis

Table 5. Comparison of Models

Model	GLM		INLA
	AIC	BIC	DIC
Poisson	8804.487	8814.851	-8084.5
Negative Binomial	611.767	623.43	612.56

Comparison of models using AIC and BIC evaluation criteria for GLM models. Meanwhile, the INLA approach uses DIC evaluation. The lower the evaluation criteria value, the better the model is at balancing data fit and model complexity. Table 5 shows the model evaluation results, where the AIC and BIC values of the negative binomial GLM model are lower than those of the Poisson GLM model, with values of 611.767 and 623.43, respectively. This indicates that the negative binomial distribution can balance complexity and data suitability better than the Poisson distribution. Negative binomial is also able to suppress data overdispersion and capture the model well. This study is in line with the literature, which shows that GLM models with negative binomial distribution are often better for data with high overdispersion (30).

The results of the negative binomial GLM model show that contraceptive use can reduce births. This finding is consistent with the theory of family planning programs, whereby increased contraceptive use can reduce the probability of conception. Empirically, several studies have shown similar results. In a study conducted by Rizkianti et al., contraceptive use was found to be the most effective factor in reducing fertility (31). Contraceptive use allows women to regulate the spacing and number of births, as well as delay their first pregnancy. According to a study by Majumder and Ram, contraceptive use among poor women led to a 13% decline in births, while among non-poor women, it led to a 6% decline in births from 1997 to 2007 (32). This proves that government policies on

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family planning are still effective in reducing births in Indonesia.

The percentage of women in the workforce has a significant negative effect on the number of births, both in the GLM and INLA approaches. This supports the statement that women working can reduce the number of births. The results of this study are in line with the research by Maulida et al., which shows that women's participation in the labor market has a significant negative impact on fertility rates (5). This condition occurs because working women tend to plan their births carefully to fit their work commitments (33). Limited time and energy available to care for children force them to balance their roles as workers and housewives (34). This situation often encourages working women to delay or reduce the number of children they have without sacrificing their careers or the quality of childcare. The number of working women may increase due to economic factors such as rising living costs and family economic needs. In addition, it is also influenced by changes in norms, especially society's views on gender equality, which make women's roles in the workforce more acceptable.

On the other hand, the results of the GLM model show that the percentage of young people aged 25-30 years old has a significant negative correlation with births. Marriage at the age of 25 and above can provide a biological age limit for pregnancy compared to marriage at the age of 10-24 years, which has a longer reproductive age. According to research conducted by Ekoriano et al., the age of 25 for women is the minimum age that is good for giving birth to an average of less than 3 children (35). Research in Uganda states that delaying marriage until above the age of 20 can change sexual behavior and birth rates (36). In addition to reducing the number of births, delaying marriage until a certain age can have a positive impact on the development of reproductive organs so that they are ready for childbirth and can reduce the risk of maternal mortality (37).

Overall, this study provides a deeper understanding of the influence of demographic and non-demographic factors on the number of births. This study shows that the use of contraception among PUS, working women, and those married between the ages of 25 and 30 can help reduce the number of births. The results of the model show that the most influential factor is working women. This can be used as the main focus of government policy in efforts to reduce births.

CONCLUSION

Based on the study, the negative binomial distribution is better for analyzing the number of births in West Java Province than the Poisson distribution. This can be seen from the lower AIC, BIC, and DIC values compared to the Poisson distribution. Based on the GLM and INLA model results, a significant negative relationship was found in working women. This confirms that, in addition, the GLM model found a negative effect of contraceptive use on births. However, this finding has not been sufficiently proven using the INLA approach. A similar finding was found in the 25-30 age group, which showed a significant negative relationship in the GLM but no clear evidence in the INLA approach. Meanwhile, other factors such as GRDP growth rate, gender empowerment index, percentage of youth with marital status, and percentage of youth with college degrees did not provide sufficient evidence to state that these factors had a significant effect.

In practical terms, these results can be used as a basis for the West Java provincial government to plan more targeted population growth control strategies. The finding that female labor force participation is the most influential factor indicates that policies

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supporting women's economic empowerment and gender equality are effective interventions in reducing birth rates. Further research is recommended to expand the analysis using panel data to observe how factors affect births over time. In addition, future research could explore other demographic and non-demographic factors to deepen understanding of the factors influencing births.

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StatMat
Jurnal Statistika dan Matematika
STATMAT (Jurnal Statistika dan Matematika)
P-ISSN: 2655-3724 E-ISSN: 2720-9881
Vol. 8, No. 2, August 2026
5th article, Pages: 246 – 257
DOI: https://doi.org/10.32493/sm.v8i2.55544

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