Contents lists available at DJM

DESIMAL: JURNAL MATEMATIKA

p-ISSN: 2613-9073 (print), e-ISSN: 2613-9081 (online), DOI 10.24042/djm

http://ejournal.radenintan.ac.id/index.php/desimal/index

Application of negative binomial regression in analyzing factors that influence stunting in toddlers

Allifiyani Tamimi[1,*], Ismail Husein[2]

Universitas Islam Negeri Sumatera Utara Medan, Indonesia

ARTICLE INFO

Article History

Received : 01-02-2024
Revised : 15-03-2024
Accepted : 09-04-2024
Published : 30-04-2024

Keywords:
Binomial Regression; Negative ; Poisson Regression; Stunting.

*Correspondence: E-mail: allifiyani0703201042@uinsu.ac.id

Doi: 10.24042/djm.v7i1.22070

ABSTRACT

Stunting is a growth and development disorder caused by a lack of nutrition. This research aims to determine the significant factors that influence cases of stunting among toddlers in North Sumatra province in 2022. By using Negative Binomial Regression, we obtained factors that have a significant influence on the incidence of stunting among toddlers in North Sumatra province. The research results obtained show that the variables of the number of toddlers who are given exclusive breastfeeding, the number of toddlers who have inadequate access to sanitation, and the number of toddlers who receive Complete Basic Immunization will have a significant effect on stunting cases in toddlers in Sumatra Province in 2022. This can be seen from the P-values of each variable that significantly influences the incidence of stunting in toddlers: 0.0285 (x1), 0.0525 (x3), and 0.0452 (x6).

http://ejournal.radenintan.ac.id/index.php/desimal/index

INTRODUCTION

The high percentage of malnutrition among children under five and those old enough to enter school, both male and female, indicates that Indonesia is experiencing a serious nutritional crisis (Tiara, Aidi, Erfiani, & Rachmawati, 2023). A nation is deemed advanced if it possesses excellent human resources, which are closely connected to health-related programs (Safitri, HG, & Devianto, 2014). Mothers' and children's efforts are the first and most important aspect in the development of health (Aipassa, Wattimena, & Haumahu, 2023). Good human beings will therefore be produced by healthy children. In an effort to develop great human resources, toddlerhood—especially the toddler years—is prioritized (Widya, 2022). This is the most important period in the human development process to forecast how well children will grow and develop (Agresti, 2007).

Stunting has the capacity to exacerbate poverty, increase inequality, and obstruct economic expansion (Sari & Harianis, 2020). Stunting is a form of development failure called "grow faltering," which happens when an infant accumulates inadequate nutrition from conception until the age of 24 months (Sari, Ratnawati, & Marsanti, 2023). This will become problematic if catch-up growth isn't achieved quickly enough. Stunting is a chronic malnutrition problem brought on by extended periods of insufficient dietary intake from foods that do not meet nutritional requirements. It may start when the fetus is still inside the mother and not show up until the child is two years old (Nababan, 2023). The age, gender, height, and body length of the toddler are taken into consideration while measuring stunting. Stunting can be challenging to identify because children's height and body length are frequently not assessed in society (Doy, Ngura, & Ita, 2021). The Trend of Nutritional Status of Indonesian Toddlers shows a considerable decline in all nutritional status indicators: stunting, wasting, underweight, and overweight (Sauddin, Auliah, & Alwi, 2020). Stunting indicators based on Basic Health Research Results (RIKESDAS) from 2013 indicate that the prevalence of stunting is 37.6% countrywide; however, it decreased to 30.8% in 2018. The Indonesian Nutrition Status Survey (SSGI) data show that the stunting indicator fell to 21.6% in 2022 from 24.4% in 2021. Based on the present percentage, the annual stunting rate is decreasing.

Research is being conducted to identify the factors that influence the prevalence of stunting in order to prevent the number of toddlers classified as stunted from increasing (Esha, Mubin, & Hakim, 2023). The government can utilize this as assessment material to monitor societal conditions and factors that are continuing to lead to an increase in stunting rates. By actively preventing stunting, parents and the community can also increase knowledge of healthy lifestyles and prevent stunting (Zubedi, Aliu, Rahim, & Oroh, 2021). The North Sumatra administration has decided to establish the stunting rate at 18% in 2023, down from 21.1% in 2021. By 2024, the rate is expected to drop to 14%. By making it simpler to prevent these contributing factors, this goal will help reduce the target for the prevalence of stunting in North Sumatra (Sinaga & Asfur, 2021).

Stunting-related factors can be found statistically using negative binomial regression. Similar to Poisson regression, negative binomial regression is a method for examining the relationship between the response and explanatory variables (Hendraswari, Purnamaningrum, Maryani, Widyastuti, & Harith, 2021). Negative binomial regression, on the other hand, provides more freedom because it does not require a match between the variance and mean values (Komalasari, Supriati, Sanjaya, & Ifayanti, 2020). Therefore, a model can be constructed, and the relationship between the number of people who suffer from stunting and the factors influencing its spread can be examined using negative binomial regression analysis (Utami, 2013). Using Negative Binomial Regression to model counted data is another method for reducing overdispersion. The aim of this research is to determine the significant factors influencing stunting in children in North Sumatra Province by negative binomial regression.

METHOD

The North Sumatra Provincial Health Service provided the secondary data used in this study. The number of cases of stunting in 33 North Sumatra Province districts and cities, as well as the factors influencing stunting in 2022, are statistics used. Among the study's variables are the number of low birth weight (LBW) babies, the number of infants who are exclusively breastfed, the number of people who lack access to sanitary facilities, the percentage of young women who used blood enhancement tablets (TTD), the number of pregnant women who used TTD, and the number of toddlers who have received all recommended vaccinations. With the aid of Rstudio software, the data was examined using negative binomial regression.

Multicollinearity Test

The multicollinearity test is used to determine whether certain independent variables in a model are similar to other independent variables. If the dependent variables in a model are comparable, there will be a significant correlation between an independent variable and other independent variables (Yuwanti, Mulyaningrum, & Susanti, 2021). If the tolerance value is not less than 0.1 and the VIF value is less than 10, multicollinearity can be detected using the VIF value. In light of this, multicollinearity is absent from the model. You may write the VIF formula like this:

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

Poisson Regression Model

An application that explains the link between the independent and dependent variables is the Generalized Linear Model (GLM). The Poisson regression model is a type of nonlinear regression model that is based on the Poisson distribution. It is expected that the dependent variable is count or discrete data with equidispersion (Aini & Achmad, 2022). The following is the formula for modeling Poisson Regression:

$$\ln(\mu_i) = \eta_i = \beta_0 + \beta_1 X_{1i} + \cdots + \beta_p X_{ip}$$

$$\mu_i = \exp(\beta_0 + \beta_1 X_{1i} + \cdots + \beta_p X_{ip}) \quad (2)$$

Overdispersion

The assumption of equidispersion, or the equivalency of the variance and mean of the dependent variable, is one of the requirements for the Poisson regression model. Nevertheless, data with a variance larger than the mean (overdispersion) are frequently discovered when counting data is analyzed (Winata, 2023). The equidispersion assumption states that the average value of the response variable and its variance value must be equal (Widyaningsih, Didah, Sari, Wijaya, & Rinawan, 2021). Because of a phenomenon known as overdispersion, which is brought about by variations in the data's variance and average values (Fitrial & Fatikhurrizqi, 2021). Frequently occurs in studies, making the equidispersion assumption unfulfilled. If the deviation value is larger than one when divided by the degree of freedom value, this indicates an overdispersion case. Other indicators of overdispersion include the Pearson chi-square value. The deviation equation has the general form given below (Habiba, 2021):

$$D = 2\sum_{i=1}^{n}\left[y_i ln\left(\frac{y_i}{\hat{y}_i}\right) - (y_i - \hat{y}_i)\right] \quad (3)$$

The Pearson Chi-Square value is obtained from the following equation:

$$X^2 = \sum_{i=1}^{n}\frac{(y_i - \hat{y}_i)}{\hat{y}_i} \quad (4)$$

Negative Binomial Regression Model

The Poisson-gamma mixed distribution, an application of GLM that explains the relationship between variables, both dependent and independent, is the source of the negative binomial regression (Nugroho, Sasongko, & Kristiawan, 2021). When modeling data, negative binomial regression is typically employed with count data as the response variable. As an alternative, consider this when dealing with overdispersion (var > mean) in Poisson regression.

Assume that it denotes the value of the response variable for the i-th observation, and that the vector of variable values for the i-th observation is represented by i = 1, 2, ..., n. It is assumed that the multiple response variable in the negative binomial regression model has the following expression:

$$ln(\mu_i) = \beta_0 + \beta_1 X_{1i} + \cdots + \beta_k X_{ik}\varepsilon_i$$
$$(\mu_i) = exp(\beta_0 + \beta_1 X_{1i} + \cdots + \beta_k X_{ik}\varepsilon_i) \quad (5)$$

Where :
$\mu_i =$ the expected value of y_i which has a Negative
$\beta_0 =$ constant value
$X_{1i}, X_{2i}, \dots, X_{ik} =$ value of the i − th independent variable
$\beta_1, \beta_2, \dots, \beta_3 =$ coefficient value
$\varepsilon_i =$ error fot the − th observation

Negative Binomial Regression Parameter Test Statistics

To find out how predictor variables affect the response variable, parameter testing is done. Partial and concurrent parameter testing is done (Saadah, 2020). The simultaneous test seeks to determine how the response variable is affected by the predictor variables taken together (Fathurahman, 2022). The likelihood ratio test was used for simultaneous testing using the following hypothesis (Yunardi, Maiyastri, & Yozza, 2021):

$$H_0 : \beta_1 = \beta_2 = \cdots = \beta_3 = 0$$
$$H_1 : thereis\ at\ least\ one, with\ j = 1,2, \dots, k$$

The likelihood ratio test is used in this assessment, and the test statistics are as follows:

$$G = -2ln\left[\frac{L(\hat{\omega})}{L(\hat{\Omega})}\right] = 2ln(\hat{\Omega}) - 2ln(\hat{\omega}) \quad (6)$$

For a basic model with no independent variables, the likelihood value is $L(\hat{\omega})$, and for the full model with independent variables, it is the likelihood value.

To make a reject decision, H_0, you can see if the value is $G > x^2_{(\alpha,v)}$. This is because the test statistic G follows a Chi-Square distribution. The v value is obtained from the number of parameters in the model. The values $x^2_{(\alpha,v)}$ can be seen in the Chi-Square table. To determine how each independent variable affected the dependent variable separately, a partial Wald test was used. Meanwhile, partial testing was carried out using the Wald test, with the following hypothesis (Yunardi et al., 2021):

$$H_0 : \beta_j = 0$$
$$H_1 : \beta_j \neq 0$$

With j = 1, 2, …, k., with Wald test statistics as follows (Fauziah, 2022):

$$W_{count} = \frac{\hat{\beta}_j}{SE(\hat{\beta}_j)} \quad (7)$$

With 1, 2, …, k, and $\hat{\beta}_j$ are the estimator values of β_j, as well as $SE(\hat{\beta}_j)$ the *standard error* from $\hat{\beta}_j$.

The decision taken for the Wald test is to reject H_0 if $p - value < \alpha$ or use the value Wcount with the decision to reject H_0. If the value $W_{count} > Z_{\alpha/2}$ or value $W_{count} > -Z_{\alpha/2}$, the value $Z_{\alpha/2}$ can be seen in the normal distribution table. The α value used in this research is 5%.

RESULTS AND DISCUSSION

Descriptive Research Data

The maximum value, lowest value, average, and variance of descriptive statistics are used to present descriptive study data. Table 1 displays the results of computations made with the R programming language to provide descriptive statistics.

Table 1. Descriptive statistics

Variable	Mean	Variant	Min	Max
Percentage of Number of Stunting Cases (Y)	24.4545	2.3181	7	39
Number of babies given exclusive breast milk (X1)	2494,182	4272824.53	210	7639
Number of babies with low birth weight (X2),	39.2	5331.5	0	382
Number of Inappropriate Sanitation (X3)	25247	1948610	209	228286
Percentage of young women who received Blood Supplement Tablets (TTD) (X4)	31	492.14	0.16	84.56
Number of pregnant women who consume Blood Supplement Tablets (TTD) (X5),	3119	10290488	119	14958
Number of Toddlers who received Complete Basic Immunization (X6).	6344	650005992	187	36944

The percentage of stunting in North Sumatra in 2022 was recorded at 21.1. With a prevalence of 39.4 for stunting, the distribution of the greatest level of stunting in 2022 for each district or city in North Sumatra in the South Tapanuli Regency. Meanwhile, the lowest number of stunting cases occurred in North Labuhan Batu Regency, with the number of stunting cases being 7.3 percent. Based on the results of the 2022 SSGI survey, it was recorded that in North Sumatra, the highest number of stunts was in South Tapanuli Regency.

Multicollinearity Test

To find out if some independent variables in a model are similar to other independent variables, the multicollinearity test is required. Meanwhile, perform the following multicollinearity test as a prerequisite to moving forward with the overdispersion test in the Poisson regression model:

Table 2. VIF value

Predictor Variables	VIF
X_1	1.301701
X_2	1.123189
X_3	1.750594
X_4	1.888809
X_5	1.253441
X_6	1.253441

Since there is no multicollinearity across the predictor variables, it is worthwhile to include the VIF values for each variable in Table 2 when creating the Poisson and Negative Binomial regression models. These values are all less than 10.

Poisson Regression Model

Parameter estimates for the Poisson regression model can be found in Table 3. This information was generated using Rstudio software. Deviance: 75; degrees of freedom: 32; Dispersion ratio: 51.79; AIC: 230.4.

So the Poisson regression model is obtained as follows:

$$ln(\mu_i) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6$$

$$(\mu_i) = exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6)$$

$$(\mu_i) = exp\,(3.150 + 5.058 \times 10^{-5} + 8.615 \times 10^{-4} - 2.682 \times 10^{-6} + 7.718 \times 10^{-4} + 1.505 \times 10^{-6} - 1.405 \times 10^{-5})$$

Table 1. Estimated values of Poisson Regression Model parameters

P	Estimate	Standard Error	Z value	$Pr(>\|Z\|)$
β_0	3.150	1.170×10^{-1}	26.908	<2e-16***
β_1	5.058×10^{-5}	1.884×10^{-5}	2.685	0.00725**
β_2	8.615×10^{-4}	4.859×10^{-4}	1.773	0.7622 .
β_3	-2.682×10^{-6}	1.166×10^{-6}	-2.300	0.02144*
β_4	7.718×10^{-4}	1.840×10^{-3}	0.419	0.667488
β_5	1.505×10^{-6}	1.565×10^{-5}	0.096	0.92339
β_6	-1.405×10^{-5}	5.939×10^{-6}	-2.366	0.01800*

Table 3 displays the five independent variables that have a significant effect on the response at the 5% level of significance. These variables include the number of babies given exclusive breast milk (x1), the number of babies with low birth weights (x2), the number of infants with inadequate access to sanitation (x3), the percentage of young women who received Blood Supplement Tablets (TTD) (x4), the number of pregnant women who took Blood Supplement Tablets (x5), and the number of toddlers who received Complete Basic Immunization (x6).

Overdispersion

Before continuing the analysis using negative binomial regression, first carry out a dispersion test on Poisson regression with the following formula:

$$\emptyset = \frac{deviance\ value}{df}$$

$$\emptyset = \frac{51.791}{26}$$

$$\emptyset = 1.991$$

Based on the previously provided data, the deviation value divided by the degree of freedom value is 1.991. If the deviation value divided by the degrees of freedom is greater than 1, the Poisson regression model indicates overdispersion. The Poisson regression model performs worse in the presence of overdispersion due to its high error rate.

Negative Binomial Regression Model

The following is the Negative Binomial regression model that is derived from the analysis that was done:

$$\ln(\mu) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6$$

$$(\mu) = exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6)$$

$$(\mu) = \exp\,(3.148 + 0.00005144X_1 + 0.0008663X_2 - 0.000002705X_3 + 0.0007416X_4 + 0.000001213X_5 - 0.00001383X_6)$$

To use the model above, a model suitability test must first be carried out.

Fit of Negative Binomial Regression Models

By dividing the deviation value by the degrees of freedom, one can determine whether the negative binomial regression model is appropriate. This yields the following results:

Table 4. Fit of Negative Binomial Regression Models

Model	$Deviance/df$
Poisson Regression	51.791/26=1.991
Negative Binomial Regression	36.044/26=1.386

The negative binomial regression model has a lower deviation value than the Poisson regression model, as seen in Table 4. This implies that the best choice for handling overdispersion scenarios is the negative binomial regression model.

Significance Test of Negative Binomial Regression Parameters

Both partial and simultaneous tests were done after getting the negative binomial regression model.

a) Simultaneous Tests of Models

Simultaneous test results (model feasibility) in negative binomial regression with the following hypothesis:

$H_0: \beta_j = \beta_1 = \beta_2 = \cdots = \beta_5 = 0$ (there is no influence of independent variables on stunting).

H_1: there is at least one j with $\beta_1 \neq 0\,; j = 1, 2, \ldots, 5$ (at least one independent variable that influences stunting).

Table 5. Simultaneous Test of the Negative Binomial Regression Model

Likelihood Ratio Chi-Square (G)	db	p-value
10.551	5	0.01442

Based on Table 5, the statistical value G is 10.551 and *p-value* is 0.01442, where the G value is smaller than $X^2_{(0.05:5)} = 11.0705$ and P-value is less than the given value. Consequently, the overall result of the negative binomial regression model test is acceptable, showing that at least one parameter has no discernible impact on the number of cases of stunting.

b) The following hypothesis is used to examine the partial significance of parameters after conducting simultaneous tests:

$H_0: \beta_j = 0$ (the independent variable has no effect on the dependent variable).

$H_1: \beta_j = 0$ (independent variable that influences the dependent variable).

Table 6. Negative Binomial Partial Regression Test

Variable	$\hat{\beta}_j$	*Std. error*	Z_{count}	*p-value*
X_1	0.00005144	0.00002348	2.190	0.0285*
X_2	0.0008663	0.0006077	1.425	0.1540
X_3	-0.000002705	0.000001395	1.939	0.0525 .
X_4	0.0007416	0.002254	0.329	0.7421
X_5	0.000001213	0.00001905	0.064	0.9492
X_6	-0.00001383	0.000006908	-2.003	0.0452*

Based on Table 6, it is known that the variables X_1, X_3, and X_6 have a value of Z_{count} that is greater than $Z_{\frac{\alpha}{2}} = 1.96$, *the p-value* which is smaller than the value of $\alpha = 0.05$ which means H_0 is rejected. So, it can be concluded that the variables that have a significant influence and contribute to the dependent variable (the number of stunting cases) are the number of babies who are given exclusive breast milk, the number of infants who have inadequate access to sanitation, and the number of toddlers who receive complete basic immunization.

Negative binomial regression modeling was again performed, this time only incorporating significant variables, as it was determined from the partial test mentioned above that the variables X_1, X_3, and X_6 are the significant ones. The following is the creation of a negative binomial regression model based on the analysis's findings:

$$\ln(\hat{\mu}_j) = \beta_0 + \beta_1 X_1 + \beta_3 X_3 + \beta_6 X_6$$

$$(\hat{\mu}_j) = exp(\beta_0 + \beta_1 X_1 + \beta_3 X_3 + \beta_6 X_6)$$

$$(\hat{\mu}_j) = \text{exp}\ (3{,}197 + 5{,}259 X_1 - 2{,}650 X_3 - 1{,}229 X_6)$$

According to the interpretation of the resulting negative binomial regression model, the number of infants receiving exclusive breast milk, the number of babies having access to subpar sanitation, and the number of toddlers receiving Complete Basic Immunization equal exp

(3,197) = 24.45 = 24 persons when there are instances of stunting.

Table 7 displays the optimal model generated by the negative binomial regression model, which is as follows:

Table 7. Results of Akaike Information Criterion (AIC)

Regression Model	AIC value
Negative Binomial	229.8
Negative Binomial with significant variables $(X_1, X_3\ and\ X_6)$	226.1

The Negative Binomial Regression Model with Significant Variables X_1, X_3, and X_6 is the best model, according to Table 7. This is because the negative binomial regression model's AIC value, 226.1 < 229.8, is X_3 smaller X_6 than the negative binomial regression model's AIC value with significant variables X_1.

CONCLUSIONS AND SUGGESTIONS

Based on the problem formulation described previously, the research findings produce the following conclusions. The negative binomial regression model for under-five stunting cases in North Sumatra Province in 2022 is as follows: $\boldsymbol{(\mu) = \exp\,(3.148 + 0.00005144X_1 + 0.0008663X_2 - 0.000002705X_3 + 0.0007416X_4 + 0.000001213X_5 - 0.00001383X_6)}$. Variables relevant to cases of toddler stunting in North Sumatra Province in 2022 were identified based on analysis using negative binomial regression. These variables include the number of babies who receive exclusive breast milk (X_1), the number of people with inadequate access to sanitation (X_3), and the number of toddlers who receive complete basic immunization (X_6).

Future research should add other predictor variables that can prevent stunting in toddlers. It is hoped that by knowing the variables that influence under-five stunting cases in North Sumatra Province, related parties can be more optimal in carrying out preventive measures or minimizing under-five stunting cases in North Sumatra Province by paying attention to each district or city.

REFERENCES

Agresti, A. (2007). *An introduction to categorical data analysis*. John Wiley & Sons, Inc.

Aini, Z. T., & Achmad, A. I. (2022). Penerapan regresi binomial negatif dalam memodelkan angka kelahiran remaja usia 15-19 tahun di indonesia pada tahun 2017. *Bandung Conference Series: Statistics*, *2*(2), 87–95. https://doi.org/10.29313/bcss.v2i2.3233

Aipassa, A. D., Wattimena, A. Z., & Haumahu, G. (2023). Analisis faktor-faktor yang mempengaruhi jumlah penyakit kusta di provinsi maluku dengan menggunakan regresi binomial negatif. *Jurnal Matematika, Statistika Dan Terapannya*, *2*(2).

Doy, E., Ngura, E. T., & Ita, E. (2021). Analisis faktor-faktor penyebab terjadinya stunting pada anak usia dini di kabupaten ngada. *Jurnal Citra Pendidikan*, *1*(1). https://doi.org/10.38048/jcp.v1i1.167

Esha, D., Mubin, A., & Hakim, F. (2023). Mengenal lebih dalam ciri-ciri stunting, cara pencegahannya, dan perilaku hidup sehat dan bersih. *Journal of Chemical Information and Modeling*, *2*(6).

Fathurahman, M. (2022). Regresi binomial negatif untuk memodelkan kematian bayi di kalimantan timur. *Eksponensial*, *13*.

Fauziah, N. F. (2022). Pemodelan poisson dan binomial negatif untuk menganalisa faktor penyebab angka kejadian abses gusi. *Jurnal Keperawatan Silampari*, *6*(1), 265–273.

https://doi.org/10.31539/jks.v6i1.3789

Fitrial, N. H., & Fatikhurrizqi, A. (2021). Pemodelan jumlah kasus covid-19 di indonesia dengan pendekatan regresi poisson dan regresi binomial negatif. *Seminar Nasional Official Statistics*, *2020*(1). https://doi.org/10.34123/semnasoffstat.v2020i1.465

Habiba, H. (2021). *Analisis faktor-faktor penyebab penyebaran penyakit kusta di sulawesi selatan tahun 2018 menggunakan regresi binomial negatif*.

Hendraswari, C. A., Purnamaningrum, Y. E., Maryani, T., Widyastuti, Y., & Harith, S. (2021). The determinants of stunting for children aged 24-59 months in kulon progo district 2019. *Kesmas: National Public Health Journal*, *16*(2). https://doi.org/10.21109/kesmas.v16i2.3305

Komalasari, K., Supriati, E., Sanjaya, R., & Ifayanti, H. (2020). Faktor-faktor penyebab kejadian stunting pada balita. *Majalah Kesehatan Indonesia*, *1*(2), 51–56. https://doi.org/10.47679/makein.202010

Nababan, N. M. (2023). Factors influencing stunting incidence. *International Journal Of Health Science*, *3*(3). https://doi.org/10.55606/ijhs.v3i3.2498

Nugroho, M. R., Sasongko, R. N., & Kristiawan, M. (2021). Faktor-faktor yang mempengaruhi kejadian stunting pada anak usia dini di indonesia. *Jurnal Obsesi : Jurnal Pendidikan Anak Usia Dini*, *5*(2). https://doi.org/10.31004/obsesi.v5i2.1169

Saadah, N. (2020). Modul deteksi dini pencegahan dan penanganan stunting. In *Scopindo Media Pustaka*.

Safitri, A., HG, I. R., & Devianto, D. (2014). Penerapan regresi poisson dan binomial negatif dalam memodelkan jumlah kasus penderita aids di indonesia berdasarkan faktor sosiodemografi. *Jurnal Matematika UNAND*, *3*(4), 58. https://doi.org/10.25077/jmu.3.4.58-65.2014

Sari, I. C., Ratnawati, R., & Marsanti, A. S. (2023). Faktor yang berhubungan dengan kejadian stunting pada balita usia 24-36 bulan. *Jurnal Ilmu Kesehatan*, *11*(2), 148. https://doi.org/10.32831/jik.v11i2.451

Sari, N. I., & Harianis, S. (2020). Analysis of factors affecting the incidence of stunting in toddlers. *Health Journal*.

Sauddin, A., Auliah, N. I., & Alwi, W. (2020). Pemodelan jumlah kematian ibu di provinsi sulawesi selatan menggunakan regresi binomial negatif. *Jurnal MSA (Matematika Dan Statistika Serta Aplikasinya)*, *8*(2). https://doi.org/10.24252/msa.v8i2.17409

Sinaga, N., & Asfur, R. (2021). Penguatan dan edukasi keluarga sebagai upaya menekan angka stunting dalam program kependudukan, keluarga berencana dan pembangunan keluarga (kkbpk) di sumatera utara. *JURNAL PRODIKMAS Hasil Pengabdian Kepada Masyarakat*. https://doi.org/10.30596/jp.v6i1.7194

Tiara, Y., Aidi, M. N., Erfiani, E., & Rachmawati, R. (2023). Overdispersion handling in poisson regression model by applying negative binomial regression. *BAREKENG: Jurnal Ilmu Matematika Dan Terapan*, *17*(1), 0417–0426. https://doi.org/10.30598/barekengvol17iss1pp0417-0426

Utami, T. W. (2013). Analisis regresi binomial negatif untuk mengatasi overdispersion regresi poisson pada kasus demam berdarah dengue. *Jurnal Statistika*, *1*(2).

Widya. (2022). Analisis faktor predictor kejadian stunting pada balita di kelurahan bandarharjo semarang. *Skripsi Fakultas Keperawatan*.

Widyaningsih, C. A., Didah, D., Sari, P., Wijaya, M., & Rinawan, F. R. (2021). Identifikasi faktor-faktor kejadian stunting. *Jurnal Kebidanan Malahayati*, *7*(2). https://doi.org/10.33024/jkm.v7i2.2854

Winata, H. M. (2023). Mengatasi overdispersi dengan regresi binomial negatif pada angka kematian ibu di kota bandung. *Jurnal Gaussian*, *11*(4), 616–622. https://doi.org/10.14710/j.gauss.11.4.616-622

Yunardi, D. A., Maiyastri, M., & Yozza, H. (2021). Pemodelan penderita stroke dan diabetes melitus di kota padang dengan model regresi logistik biner bivariat. *Jurnal Matematika UNAND*, *9*(4), 270. https://doi.org/10.25077/jmu.9.4.270-277.2020

Yuwanti, Y., Mulyaningrum, F. M., & Susanti, M. M. (2021). Faktor-faktor yang mempengaruhi stunting pada balita di kabupaten grobogan. *Jurnal Keperawatan Dan Kesehatan Masyarakat Cendekia Utama*, *10*(1). https://doi.org/10.31596/jcu.v10i1.704

Zubedi, F., Aliu, M. A., Rahim, Y., & Oroh, F. A. (2021). Analisis faktor-faktor yang mempengaruhi stunting pada balita di kota gorontalo menggunakan regresi binomial negatif. *Jambura Journal of Probability and Statistics*, *2*(1), 48–55. https://doi.org/10.34312/jjps.v2i1.10284