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NEGATIVE BINOMIAL REGRESSION ANALYSIS OF STUNTING DETERMINANTS IN TODDLERS: ACHIEVING OPTIMAL NUTRITION IN WEST JAVA, INDONESIA

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Abstract: Stunting in children represents a serious public health concern in developing countries, impeding nutritional growth and overall well-being. Its causes are multifaceted, including malnutrition, psychosocial and social factors. The consequences of stunting extend beyond individual health, contributing to broader socio-economic decline, diminished quality of life, and long-term health deficits. As a critical indicator within the Sustainable Development Goals (SDGs), Indonesia has made notable progress in reducing stunting prevalence, from 21.6% in 2022 to 17.8% in 2023, moving closer to the national target of 14%. Nevertheless, the target remains unmet, underscoring the ongoing need for enhanced prevention strategies. This study investigates the effects of key determinants, including low birth weight, exclusive breastfeeding, vitamin A supplementation, and the availability of healthcare services, on stunting in West Java. Negative binomial regression was applied to account for the over-dispersed nature of the stunting data, offering a more robust alternative to Poisson regression when variance exceeds the mean. The findings indicate that low birth weight and vitamin A supplementation are significant predictors of stunting. A thorough understanding of these factors is essential for designing and implementing effective interventions to mitigate stunting.

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1. INTRODUCTION

Stunting in children under five years of age is a significant public health issue, particularly in developing countries. Stunting, characterized by impaired physical development, reflects inadequate nutritional intake during the critical first 1,000 days of life. Malnutrition begins in utero and continues in the early postnatal period, though the visible effects of stunting often only manifest after the age of two. The World Health Organization (WHO) defines stunting as a condition marked by delayed growth and development in children under two years of age. This condition is primarily driven by malnutrition, infections, and insufficient psychosocial support. Stunting is prevalent in developing countries, where malnutrition is a major public health challenge [1]. Children under five who experience stunting are at increased risk of disease, cognitive and developmental impairments, and long-term health complications. Moreover, stunting has far-reaching societal consequences, impeding economic growth, perpetuating poverty, and exacerbating social inequality [2].

Stunting is a key indicator within the Sustainable Development Goals (SDGs), particularly under Goal 2: "End hunger, achieve food security, improved nutrition, and promote sustainable agriculture". The SDGs set targets to reduce the prevalence of stunting and wasting among children under five by 2025 and to eliminate all forms of malnutrition by 2030. Therefore, efforts to reduce stunting, supported by governments, communities, and educational institutions, are vital for achieving national targets, fulfilling the SDG objectives by 2030, and improving overall human well-being [3].

The Indonesian Nutrition Status Survey (SSGI) reported a stunting rate of 21.6% in 2022, which declined to 17.8% in 2023, but still exceeds the government's target of 14%. The government aims to reduce the stunting rate to 14% by 2024, as outlined in Presidential Decree Number 72 of 2021 on the Acceleration of Stunting Reduction. As illustrated in Figure 1, these findings suggest that current efforts are insufficient, emphasizing the need for intensified stunting prevention initiatives to meet the national reduction targets.

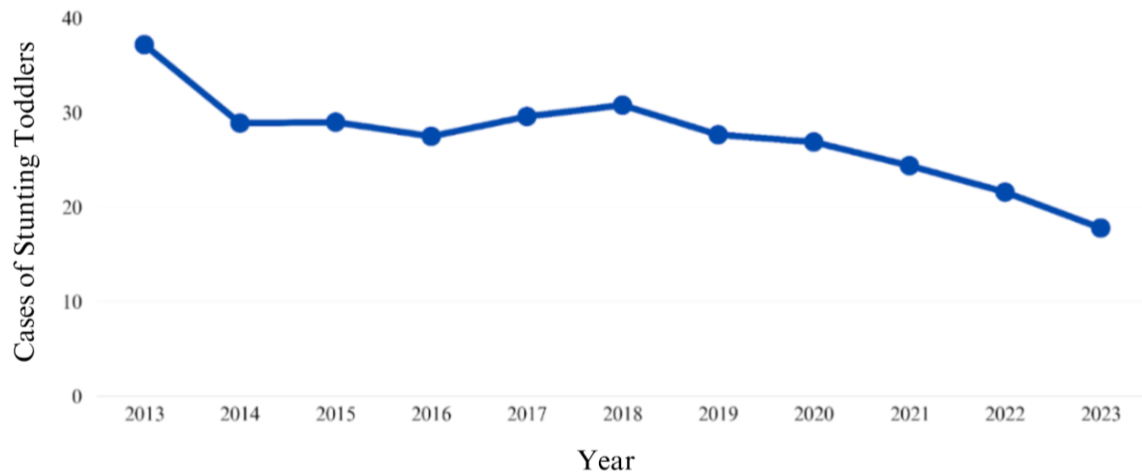

Figure 1. Prevalence of stunting in Indonesia (2013-2023)

The suboptimal management of stunting can be attributed to the complex interplay of various contributing factors. Stunting prevalence is influenced by multiple determinants, with a history of low birth weight being associated with a higher likelihood of stunting among children under five [4]. Infants born with low birth weight are particularly vulnerable to growth and developmental impairments, especially if they experience inadequate nutrition, recurrent illnesses, and insufficient access to medical care [5]. Compared to infants with normal birth weight, those with low birth weight face higher risks of mortality, developmental delays, and growth deficiencies. Consequently, low birth weight has been observed to correlate with an increased risk of stunting, making these infants more prone to stunted growth.

The Indonesian Ministry of Health (2018) identifies multiple factors that contribute to the prevalence of stunting [6]. The World Health Organization (WHO, 2013) emphasizes the complex etiology of stunting, linking its origins to various factors such as maternal health, environmental conditions, insufficient nutrition, inadequate infant and young child feeding practices, food and water insecurity, suboptimal breastfeeding, infectious diseases, and restricted access to pediatric healthcare services. Comprehending these contributing elements is crucial for formulating focused and effective measures to diminish stunting prevalence [7].

Exclusive breastfeeding plays a vital role in mitigating stunting, hence enhancing the well-being of future generation. Stunting, often associated with low birth weight and impaired physical development, continues to pose a considerable worldwide health concern [8]. Immunization is crucial for strengthening a child's immune system against infections that could impede growth, while exclusive breastfeeding delivers key nutrients required for healthy growth and development.

Collectively, these interventions are essential in alleviating stunting and fostering long-term health outcomes [9].

The WHO/UNICEF recommends that infants aged 6 to 23 months be provided with sufficient supplemental foods comprising a diverse selection of at least four food groups, including legumes, dairy, eggs, animal protein sources, and vegetables and fruits rich in vitamin A [10]. Vitamin A is essential for growth and immunological function, with deficits markedly elevating the risk of infections and mortality. Furthermore, a deficit in vitamin A can adversely affect bone health, as osteoblasts may degrade bone matrix, hence hindering growth and development [11]. Consequently, ensuring sufficient vitamin A consumption is crucial for fostering good health and averting prolonged negative consequences [12].

West Java, a province in Indonesia, continues to face significant challenges related to child stunting. According to the latest data, the prevalence of stunting in West Java was 20.2% in 2022, representing a 4.3% decrease from 2021. Despite this reduction, the data indicates that one in five children under the age of five in West Java is affected by stunting. In 2022, West Java ranked 22nd nationally in terms of stunting prevalence among children under five. These figures highlight the ongoing need for targeted interventions to further reduce stunting rates in the province.

This study aims to investigate the determinants of stunting in West Java, with a focus on exclusive breastfeeding, vitamin A intake, neonatal birth weight, and access to healthcare services. The primary objective is to evaluate the extent to which these factors contribute to stunting and to identify effective interventions for reducing stunting rates in the province. This research offers a significant contribution by providing a comprehensive analysis of localized stunting determinants, addressing gaps in existing studies that often examine these factors in isolation. The novelty of the study lies in its focus on West Java, a region with a high prevalence of stunting, and its use of the most recent data to guide targeted, context-specific interventions. Other studies related to stunting in Indonesia have been conducted in East Nusa Tenggara [13] and Java Island [14]. The findings are expected to inform public health policy by promoting evidence-based nutritional practices and improving healthcare services, ultimately aiming to reduce stunting and improve long-term child health outcomes in the region.

2. PRELIMINARIES

2.1 Poisson Regression Model

The fundamental generalized linear model (GLM) for count data is the Poisson regression model, which employs a logarithmic link function. This framework utilizes the Poisson distribution to characterize the random component of the model, making it suitable for modeling count data that reflects the frequency of occurrences within a specific time or spatial interval [15]. Poisson regression is particularly effective at analyzing the relationship between a response variable that follows a Poisson distribution and one or more predictor variables.

The Poisson distribution is appropriate for data that represents the frequency of events in a process characterized by independent occurrences and a constant mean rate. In this distribution, the mean and variance are equal, which necessitates evaluating whether this assumption holds for the dataset being analyzed [16]. If overdispersion is present where the variance exceeds the mean alternative models, such as negative binomial regression, may be more suitable for capturing the data's characteristics. The fundamental equations for the generalized linear model (GLM) utilizing a Poisson distribution are expressed as follows:

$$y_i \sim Poisson(\mu_i) \tag{1}$$

$$log(\mu_i) = X_i^T \beta \tag{2}$$

In these equations, y_i represents the observed count for the i-th observation, μ_i denotes the expected count, X_i^T is the vector of predictor variables for the i-th observation, and β represents the vector of coefficients. By applying a logarithmic transformation to the expected count, Poisson regression models the multiplicative effects of predictor variables on the response variable, thereby providing a flexible and robust framework for analyzing count data. The Poisson regression model utilizes a log link function to relate the mean of the response variable to a linear combination of the predictor variables. For a sample of observations $y_1, y_2, \dots, y_n$, the relationship can be expressed as:

$$y_i = \mu_i + \varepsilon_i = exp(X_i^T \beta) + \varepsilon_i \ ; \ i = 1,2,\dots.,n. \tag{3}$$

where μ_i is the expected value of y_i, $X_i^T\beta$ represents the linear predictor (with X_i as the matrix of predictors and β as the parameter vector), and ε_i is the error term [16]. The log-likelihood function for n independent Poisson observations is given by:

$$logL(\beta) = \sum_{i=1}^{n} \{y_i log(\mu_i) - \mu_i - log(y_i!)\} \tag{4}$$

This function forms the basis for estimating the regression coefficients. The general form of the Poisson regression model can be written as:

$$\mu_i = \exp\,(X_i^T \beta) \tag{5}$$

This formulation shows how changes in the predictor variables influence the expected count outcome μ_i.

2.2 Overdispersion

Overdispersion in Poisson regression occurs when the variance of the response variable exceeds its mean, potentially leading to erroneous conclusions. This situation results in an underestimation of the standard errors of the estimated regression parameters, which can cause certain parameters to appear statistically significant when they are not. Consequently, the model's predictions and interpretations may be misleading. Overdispersion can manifest as either apparent or true overdispersion. To identify overdispersion, the Deviance (D) value can be utilized, which acts as a likelihood ratio test comparing the fitted model to a saturated model. The deviance is normalized by the degrees of freedom and can be expressed as follows:

$$D = 2\, ln\left(\frac{L(y_i, y_i)}{L(\hat{\mu}_i, y_i)}\right) \tag{6}$$

In this equation, y_i represents the observed values of the response variable, while $\hat{\mu}_i$ indicates the estimated mean derived from the Poisson distribution. The degrees of freedom (db) are calculated using the formula $(n-k)$, where n denotes the number of observations and k signifies the number of parameters in the model. The dispersion parameter (ϕ) is computed by dividing the deviance by its degrees of freedom:

$$\phi = \frac{D}{db} \tag{7}$$

When the dispersion statistic exceeds one, it indicates the presence of overdispersion in the response variable. If true overdispersion is confirmed, several approaches can be employed to address it, including the use of generalized Poisson models or negative binomial regression models, which are specifically designed to accommodate the additional variability in the data. These methods provide more accurate modeling of count data while addressing the inherent overdispersion, ultimately enhancing the reliability of inference and predictions.

2.3 Negative Binomial Regression

Negative binomial regression is a statistical model derived from the Poisson-Gamma distribution mixture, serving as an extension of the Generalized Linear Model (GLM). This model is particularly effective for modeling count data when the response variable exhibits overdispersion. In such cases, negative binomial regression is often preferred over Poisson regression, which assumes that the mean and variance are equal. In this framework, the response variable Y is assumed to follow a negative binomial distribution, which can be understood as a Poisson distribution with a gamma-distributed mean. The probability density function (PDF) for the negative binomial distribution is given by:

$$f(y_i;\mu_i,\alpha)=\frac{\Gamma\left(y_i+\frac{1}{a}\right)}{y_i!\,\Gamma\left(\frac{1}{a}\right)}\left(\frac{1}{a\mu+1}\right)^{\frac{1}{a}}\left(\frac{a\mu_i}{\mu_i+1}\right)^{y_i},\ y_i=0,1,2,\ldots \tag{8}$$

In this equation, y_i represents the observed count, μ_i denotes the expected mean count, and α is the dispersion parameter that controls the degree of overdispersion. The negative binomial regression model is typically expressed using the logarithmic link function as follows:

$$ln(\mu_i)=X_i^T\beta \tag{9}$$

Thus, the expected value μ_i is provided in Equation (6). The log link function ensures that the predicted counts μ_i are non-negative, making it suitable for modeling count data. This method allows for the incorporation of multiple predictor variables while effectively addressing overdispersion in the data. By employing negative binomial regression, researchers can achieve more accurate parameter estimates and predictions, thereby enhancing the model's robustness and interpretability across various applied contexts.

2.4 Multicollinearity Test

The multicollinearity test is crucial for determining if independent variables in a model demonstrate significant linear correlations with each other. Multicollinearity can adversely impact a regression model by raising the standard errors of the predicted coefficients, complicating the evaluation of each predictor's unique contribution. This problem may result in erroneous findings, causing substantial predictors to seem trivial. Various techniques are employed to identify multicollinearity. One method is to analyze the Pearson correlation coefficient (r_{ij}) among predictor variables; a value of (r_{ij}) more than 0.95 signifies a strong correlation, indicating the presence of multicollinearity [17]. This method solely identifies pairwise correlations and may not comprehensively address multicollinearity in models with numerous predictors. A more thorough approach is the Variance Inflation Factor (VIF). A VIF score exceeding 10 indicates substantial multicollinearity, signifying that predictor variables lack independence. The Variance Inflation Factor (VIF) for a predictor variable j is computed using the formula:

$$VIF_j = \frac{1}{1 - R_j^2}, j = 1,2,\ldots\ldots,p \tag{10}$$

where R_j^2 is the coefficient of determination from the regression of the j-th variable against all other variables. Upon detecting multicollinearity, potential solutions encompass the elimination or amalgamation of linked variables, or the application of regularization methods like ridge regression to alleviate its impact. These measures enhance model stability and the precision of parameter estimations.

3. MAIN RESULTS

3.1 Data

This study utilizes secondary data sourced from Open Data West Java, focusing on factors that may influence the prevalence of stunting in children under five in West Java Province. The dependent variable in this study is the incidence of stunting among toddlers in each district or city in West Java (Y). These variables are expected to have a significant impact on stunting rates, where low birth weight and insufficient exclusive breastfeeding may lead to developmental challenges, while the availability of healthcare services can help mitigate these risks by providing essential medical support and interventions. The predictor variables are given as follows:

TABLE 1. Research Variables

Variable	Definition
Y	Number of Stunted Toddlers
X_1	Number of Infants with Low Birth Weight
X_2	Number of Infants under 6 Months Receiving Exclusive Breastfeeding
X_3	Number of Toddlers Given Vitamin A (12-19 months)
X_4	Number of Hospitals
X_5	Number of Health Centers

This comprehensive approach provides insights into both individual health factors (such as birth weight and breastfeeding) and broader systemic factors (such as access to healthcare facilities), helping to explain their combined effect on stunting rates in young children across West Java.

3.2 Poisson Regression Model, Multicollinearity and Overdispersion Test Results.

The Poisson regression model is applied to estimate the number of events (in this case, the number of stunted toddlers) based on the predictor variables. The general form of the Poisson regression model is expressed as:

$$\mu_i = exp(\ \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5) \tag{11}$$

For this particular analysis, the fitted model becomes:

$$\begin{aligned}\mu_i = \exp\,&((7.631e + 00) + (5.709e - 04)X_1 - (1.139e - 05)X_2 + (6.937e - 05)X_3 \\ &- (1.960e - 04)X_4 + (6.342e - 04)X_5)\end{aligned} \tag{12}$$

This equation reveals the relationship between the predictor variables $(\mathrm{X}_1, \mathrm{X}_2, \mathrm{X}_3, \mathrm{X}_4, \mathrm{X}_5)$ and the expected number of stunting cases (μ_i). The model coefficients represent the estimated log-transformed effects of each predictor variable on the response variable.

Multicollinearity occurs when predictor variables in the model are highly correlated, potentially leading to unstable estimates of regression coefficients. To check for multicollinearity, the Variance Inflation Factor (VIF) is used. A VIF value exceeding 10 typically indicates problematic multicollinearity. Table 2 presents the VIF results for the Poisson regression model:

TABLE 2. Multicollinearity test results

Variable	VIF
X_1	3.223333
X_2	4.432946
X_3	5.143933
X_4	1.849327
X_5	4.522565

Since all VIF values are below 10, there is no significant multicollinearity between the independent variables in the model. This ensures that the regression coefficients are stable, and the model's results can be interpreted with confidence. The absence of multicollinearity supports the accuracy of the Poisson model's parameter estimates. Poisson regression assumes that the mean and variance of the response variable are equal. However, when the variance significantly exceeds the mean, overdispersion occurs, which can lead to underestimating standard errors and unreliable $\mathrm{P}_{\mathrm{value}}$. To test for overdispersion, the following statistics were calculated:

TABLE 3. Overdispersion test results

Z	P_{value}	Overdispersion
3.3962	0.0003416	1087.448

Based on these results, the overdispersion estimate of 1087.448 indicates that the variance is substantially greater than the mean. The small $\mathrm{P_{value}}$ (0.0003416) strongly rejects the null hypothesis ($\mathrm{H_0}$) of no overdispersion, suggesting that the data exhibit significant overdispersion. This finding implies that the Poisson regression model is not appropriate for the data as it violates the assumption of equal mean and variance. As a result, alternative models, such as the negative binomial regression model, which accounts for overdispersion, should be considered for more accurate estimation and inference.

3.3 Results of The Negative Binomial Regression Model

To address the overdispersion observed in the Poisson regression model, a negative binomial regression model was employed. This method is suitable for count data where the variance exceeds the mean. The general form of the negative binomial regression model is as follows:

$$\mu_i = exp(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5) \tag{13}$$

A significance test was conducted to determine the effect of each predictor variable in the negative binomial regression model. The results are shown in Table 4:

TABLE 4. Significance test results

Variable	Estimate	Std.Error	Stat.Test	P_{value}
Intercept	$7.443e+00$	$2.046e-01$	36.383	$< 2e-16$
X_1	$6.317e-04$	$2.880e-04$	2.194	0.02825
X_2	$-1.785e-05$	$1.331e-05$	-1.341	0.17985
X_3	$7.440e-06$	$2.403e-06$	3.096	0.00196
X_4	$-1.354e-04$	$8.879e-03$	-0.015	0.98784
X_5	$4.473e-03$	$8.840e-03$	0.506	0.61282

The intercept has a coefficient of 7.443 with an extremely low $\mathrm{P_{value}}$ $(< 2\mathrm{e}-16)$, highlighting its strong significance in the model. The variable $\mathrm{X_1}$ (the number of low birth weight infants) has a positive coefficient of $6.317\mathrm{e}-04$ and a $\mathrm{P_{value}}$ of 0.02825, showing that this factor is statistically significant and positively associated with stunting. The number of toddlers receiving Vitamin A (X_3) is also significant, with a P_{value} of 0.00196, indicating a notable positive effect on the prevalence of stunted toddlers. In contrast, the variables (X_2), (X_4), and (X_5) have P_{value} exceeding 0.05, suggesting they do not have a statistically significant influence on stunting prevalence. These findings emphasize that (X_1) and (X_3) are central to the simplified negative binomial regression model, playing a significant role in influencing stunting cases in West Java.

Given that only X_1 and X_3 are significant, a simplified model is constructed using only these two variables:

$$\mu_i = exp(\beta_0 + \beta_1 X_1 + \beta_3 X_3) \tag{14}$$

The reduced model is:

$$\mu_i = exp((7.587e+00) + (5.426e-04)X_1 + (6.182e-06)X_3 \tag{15}$$

This simplified model focuses on the significant predictors, offering a more concise relationship between the variables and the expected number of stunted toddlers. By concentrating on the key factors, the model enhances interpretability while reducing the risk of overfitting. This streamlined approach allows for clearer insights into the determinants of stunting, specifically addressing low birth weight and improving Vitamin A supplementation. The negative binomial regression model efficiently handles overdispersion and highlights the significant factors contributing to stunting in West Java. The influence of low birth weight and Vitamin A provision suggests important opportunities for health interventions aimed at reducing stunting rates in the region.

4. DISCUSSION

The next step in this analysis is to identify the optimal model for predicting stunting cases in West Java by comparing different models using the Akaike Information Criterion (AIC). AIC is a widely used measure for model selection, where a lower AIC value indicates a better model, balancing complexity with the goodness of fit. The AIC values for the evaluated models are as follows:

TABLE 5. Akaike Information Criterion Results

Regression Model	AIC value
Poisson	27941.5
Negative Binomial	511.4444
Negative Binomial with significant variables (X_1 and X_3)	507.3834

As shown in Table 5, the negative binomial regression model that includes only the significant variables (X_1 and X_3) has the lowest AIC value of 507.3834. This indicates that this model is the most suitable for explaining stunting cases in toddlers in West Java, as it provides the best balance between simplicity and fit.

The results clearly show that the Poisson regression model, with an AIC of 27941.5, is far less suitable due to its substantially higher AIC value. This highlights the Poisson model's failure to account for overdispersion in the data, which was previously identified as an issue. In contrast, the negative binomial model performs significantly better, with an AIC of 511.4444, as it addresses overdispersion by introducing an extra parameter that accounts for the variance being greater than the mean. Furthermore, when the model is refined to include only the statistically significant variables (X_1 and X_3), the AIC decreases further to 507.3834. This indicates that simplifying the model by focusing on the key predictors improves its overall performance, making it more efficient while still capturing the critical factors influencing stunting cases.

The results of this study indicate that low birth weight and Vitamin A supplementation are key factors influencing stunting in toddlers in West Java, aligning with previous research on the subject. Batchelor, et al (2021) similarly identified low birth weight as a significant contributor to stunting, noting that underweight newborns often face early nutritional challenges that impede their growth and development. These findings reinforce the argument that improving maternal and neonatal healthcare to promote healthy birth weights can reduce the risk of stunting [18]. The findings of this study align with Usman and Masrul (2022), who similarly identified a significant correlation between Vitamin A levels and stunting. In his case-control research on stunted adolescents of Minangkabau ethnicity, Usman demonstrated that stunted adolescents had considerably lower Vitamin A levels compared to their non-stunted counterparts. This reinforces the role of Vitamin A in mitigating stunting and supports the need for targeted nutritional interventions [19].

5. CONCLUSION

The negative binomial regression model with variable selection is the most effective approach for analyzing the factors contributing to stunting in toddlers in West Java. This model identifies low birth weight (X_1) and Vitamin A supplementation (X_3) as key determinants, offering clear direction for policymakers and healthcare practitioners to develop targeted interventions to reduce stunting in the region. The data shows a strong correlation between these two factors and stunting rates. Adequate Vitamin A intake is crucial for protecting children from infections that could compromise their health, while achieving optimal birth weight is critical for healthy development, reducing the risk of malnutrition and related complications.

Focusing on early health interventions, such as ensuring sufficient Vitamin A intake and promoting healthy birth weights, can significantly reduce stunting and improve long-term developmental outcomes. By addressing these essential factors, the well-being of children in West Java can be enhanced, providing them with better opportunities for healthy growth and development.

CONFLICT OF INTERESTS

The authors declare that there is no conflict of interests.

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