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Negative Binomial Regression for Low Birth Weight (LBW) Cases in Kolaka Regency

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Keywords: Kolaka Regency, low birth weight, negative binomial regression, overdispersion

Abstract:

Low birth weight (LBW) is a major risk factor for neonatal mortality. Kolaka Regency experienced a 41.98% increase in LBW cases in 2024, necessitating an analysis of influencing factors. This study aims to model the average number of LBW cases using negative binomial regression. Data were obtained from the Kolaka District Health Office with 12 sub-districts as observation units. The dependent variable was the number of LBW cases, while independent variables included the percentage of K4 antenatal care coverage (X_1), number of pregnant women consuming 90 iron supplement tablets (X_2), and number of pregnant women with chronic energy deficiency (CED, X_3). Results showed overdispersion in the data, making negative binomial regression appropriate. Two variables significantly influenced LBW cases: the number of pregnant women consuming 90 iron supplement tablets had a negative effect ($\beta_2 = -0.0025$; $p = 0.004$), and the number of pregnant women with CED had a positive effect ($\beta_3 = 0.0231$; $p < 0.001$). Increasing consumption of 90 iron supplement tablets reduces the average number of LBW cases, while increasing the number of pregnant women with CED increases the average number of LBW cases in Kolaka Regency.

1. Introduction

Low birth weight (LBW), defined as an infant born weighing less than 2,500 grams, remains a critical global health issue and a leading cause of neonatal mortality. Data from the World Health Organization indicates that approximately 15% of all births worldwide are LBW, with 90% of these cases occurring in developing countries, including Indonesia (Yulianti & Hasanah, 2024). Infants born with LBW face a mortality rate 35 times higher than infants with normal birth weight and are at elevated risk for developmental disabilities and chronic diseases later in life, such as obesity and diabetes (WHO, 2020). These consequences underscore the importance of understanding and addressing factors contributing to LBW incidence.

Indonesia continues to grapple with a significant burden of LBW. The 2024 Indonesian Health Profile reported that 3.9% of all live births weighed at birth were LBW (Kemenkes RI, 2025). This national trend is mirrored in Southeast Sulawesi Province, where the number of LBW cases increased by 1% from 2023 to 2024 (Dinkes Sultra, 2025). Within

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the province, Kolaka Regency presents a particularly concerning situation. Based on the Kolaka Regency Health Profile, the percentage of LBW cases reached approximately 5% of total live births. In absolute terms, the number of cases surged from 131 in 2023 to 186 in 2024, a dramatic increase of 41.98% (Dinkes Kolaka, 2025). This sharp rise indicates a critical problem that requires immediate investigation to identify the determinants of LBW in the regency and develop evidence-based intervention strategies.

Previous studies have identified several factors associated with LBW incidence. Research by Pertiwi (2023) indicated that comprehensive antenatal care coverage (K4) has a negative effect on LBW. Pradana (2024) found that pregnant women who consumed fewer than 90 iron supplement tablets (iron supplementation) had a 10.88 times higher risk of delivering an LBW infant. Additionally, a study by Prihandani et al. (2022) demonstrated a significant relationship between chronic energy deficiency (CED) in pregnant women and the incidence of LBW. These findings are consistent with international research. A recent pooled analysis of national surveys in Nepal by Khanal et al. (2024) revealed that mothers who did not attend antenatal care had 1.49 times higher odds of having an LBW baby, and those who did not consume iron-folic acid supplements had 1.43 times higher odds of having an LBW baby. Furthermore, the study highlighted the synergistic protective effect of combining adequate ANC visits with iron-folic acid supplementation (Khanal et al., 2024). Similarly, research in Bangladesh emphasized that maternal malnutrition, influenced by socioeconomic and demographic factors, is a significant public health issue with direct implications for child health (Dey et al., 2024).

While these studies provide valuable insights into individual risk factors for LBW, they predominantly employ methods such as logistic regression or spatial analysis to examine relationships at the individual level. For instance, Khanal et al. (2024) successfully used logistic regression to establish the protective effects of ANC and iron supplementation against LBW at the individual level in Nepal. However, for effective public health planning and resource allocation at the regency level, it is essential to understand the factors influencing the *number* of LBW cases across different sub-districts as aggregated count data. This requires a distinct methodological approach. In statistical analysis, Poisson regression is a standard method for modeling count data, such as the number of LBW cases per sub-district. However, a key assumption of the Poisson model is equidispersion, where the mean and variance of the dependent variable are equal. Preliminary analysis of the 2024 data from Kolaka Regency reveals that the variance of LBW cases (89.91) substantially exceeds the mean (15.5), indicating the presence of overdispersion. This violation leads to underestimated standard errors and inefficient parameter estimates when using standard Poisson regression (Rahayu, 2020).

Several studies have compared alternative methods for handling overdispersed count data. Research by Prahutama et al. (2017); Haryanto & Wibowo (2022); and Ibnas et al. (2023) demonstrated that negative binomial regression provides superior results compared to generalized Poisson regression for overdispersed data based on RMSE and AIC criteria. Negative binomial regression introduces an extra parameter to model the overdispersion, making it an appropriate alternative for such data (Efendi & Yotenka, 2021; Fatmala et al., 2024). Despite these methodological advances, the specific application of negative binomial regression to model LBW cases at the regency level, particularly in the context of Kolaka with its recent sharp increase, remains underexplored in the literature.

Therefore, this study aims to address this gap by applying negative binomial regression to model the overdispersed count data of LBW cases in Kolaka Regency and to identify the factors influencing the number of cases in 2024. The novelty of this research lies in its focus on aggregated count data at the sub-district level rather than individual-level risk factors, and its application of negative binomial regression specifically to the context of Kolaka Regency, where a 41.98% increase in cases demands urgent attention. The findings are expected to provide evidence-based recommendations for health agencies and local governments to develop targeted interventions for reducing LBW incidence in Kolaka Regency.

2. Method

This quantitative study employed an ecological study design using secondary data obtained from the Kolaka District Health Office for the year 2024. The unit of analysis was the 12 sub-districts within Kolaka Regency. The dependent variable (Y) was the number of LBW cases per sub-district. The independent variables were: the percentage of comprehensive antenatal care coverage (K4) (X_1, in %), the number of pregnant women who consumed 90 iron supplement tablets (X_2, in persons), and the number of pregnant women diagnosed with chronic energy deficiency (CED) (X_3, in persons) (Dinkes Kolaka, 2025).

Data analysis proceeded in several stages. First, descriptive statistics were calculated for all variables. Second, the presence of overdispersion was formally tested. In a preliminary Poisson regression model, if the ratio of the deviance or Pearson chi-square statistic to its degrees of freedom is greater than 1, overdispersion is indicated. A significant p-value from a likelihood ratio test comparing Poisson and negative binomial models confirms this (Dappa & Guntur, 2024). Multicollinearity among independent variables was assessed using the variance inflation factor (VIF), with a VIF > 10 indicating a problem.

Given the expectation of overdispersion, a negative binomial regression model was employed. This model is an extension of the Poisson-gamma distribution and is well-suited for count data with variance exceeding the mean (Efendi & Yotenka, 2021). The general form of the model is $\mu_i = \exp(\beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i})$, where μ_i is the expected number of LBW cases in sub-district i, and β are the regression coefficients. Model parameters were estimated using the maximum likelihood estimation (MLE) method.

The significance of the model parameters was evaluated both simultaneously and partially. The simultaneous test used the likelihood ratio test (G-test) with the hypothesis H_0: $\beta_1 = \beta_2 = \beta_3 = 0$ (no independent variables collectively affect the dependent variable) (Zubedi et al., 2021). The partial test for each independent variable used the Wald test (χ^2-distributed) with the hypothesis H_0: $\beta_j = 0$ (the j-th independent variable has no individual effect) (Yuniar et al., 2025). A significance level of $\alpha = 0.05$ was used. After identifying significant variables, the model was refitted to include only these variables. The final model's goodness-of-fit was assessed using the deviance statistic, where a non-significant p-value (or deviance value less than the chi-square table value) indicates an adequate fit. All analyses were performed using R software.

3. Result and Discussion

3.1. Descriptive Statistics and Model Diagnostics

Descriptive statistics for the variables across the 12 sub-districts are presented in Table 1. The average number of LBW cases was 15.50, with a variance of 89.91. This substantial difference, where the variance is nearly six times the mean, is a classic statistical signature of overdispersion. It suggests that the occurrence of LBW is not a uniform process across the regency; rather, it is likely clustered, with some sub-districts experiencing far more cases than others due to unobserved heterogeneity in risk factors or local conditions. The number of LBW cases ranged from a minimum of 6 (Watubangga) to a maximum of 32 (Latambaga), further illustrating this spatial disparity. The independent variables also showed considerable variation across sub-districts, indicating diverse socio-health profiles that could influence birth outcomes. For instance, the number of pregnant women consuming iron supplements (X_2) showed a very high variance (13,281.18), ranging from 85 to 455 people, highlighting significant disparities in antenatal care uptake across the region. A goodness-of-fit test for Poisson distribution yielded a deviance value indicating poor fit ($p < 0.05$), confirming that the data do not follow a Poisson distribution.

Table 1. Descriptive statistics of variables

Variable	Mean	Variance	Minimum	Maximum
Y (LBW cases)	15.50	89.91	6	32
X_1 (K4 coverage, %)	70.33	186.24	48	91
X_2 (iron supplement consumption, persons)	229.50	13,281.18	85	455
X_3 (CED cases, persons)	46.25	734.93	17	96

A multicollinearity test using variance inflation factor (VIF) showed that all independent variables had VIF values below 10 ($X_1 = 1.036$, $X_2 = 1.722$, $X_3 = 1.721$), indicating no serious multicollinearity issues among predictors. This confirms that the independent variables can be included simultaneously in the regression model without distorting parameter estimates.

A formal overdispersion test using the Pearson chi-squared statistic confirmed the finding from descriptive statistics. As shown in Table 2, the test statistic was significant ($\chi^2 = 18.505$, df = 8, $p = 0.018$), indicating that the Poisson model's assumption of equal mean and variance is violated. The rule of thumb for Poisson models is that the ratio of the deviance to its degrees of freedom should be close to 1. A value exceeding 1.5, as seen here, strongly indicates overdispersion, leading to underestimated standard errors and potentially spurious significance. The likelihood ratio test comparing the Poisson model with predictors to a null model was also significant ($G = 43.005$, $p < 0.001$), confirming that the

independent variables collectively have a significant effect. This confirms that the negative binomial regression model is a more appropriate choice, as it introduces an extra parameter to explicitly model this extra variance.

Table 2. Model comparison test result

Criteria	Value	DF	P-Value
Likelihood ratio test (Poisson model vs null model)	43.005	3	<0.001
Overdispersion test (Pearson chi-squared)	18.505	8	0.018

3.2. Negative Binomial Regression Modeling

The initial negative binomial regression model, including all three predictors, revealed that the percentage of K4 coverage (X_1) was not a significant predictor ($p = 0.899$). This lack of significance, despite being identified in previous studies, is an important finding. It may be because the K4 coverage percentage is a relatively crude, high-level indicator. Its effect on LBW is likely mediated through more specific, actionable components of antenatal care, such as the consumption of iron supplements (X_2) and the management of maternal nutrition (X_3), which were already included in the model. In essence, once these specific pathways are accounted for, the overall coverage metric may not provide additional explanatory power. The inclusion of an insignificant variable can also lead to estimation inefficiency. Consequently, a more parsimonious model was fitted, including only the significant variables: the number of pregnant women consuming iron supplements (X_2) and the number of pregnant women with CED (X_3). The parameter estimates for this final model are presented in Table 3.

Table 3. Parameter estimates of the final negative binomial regression model

Parameter	Estimate	Std. Error	Z Value	P-Value
Intercept	2.1273	0.1802	11.806	<0.0001
X_2 (iron supplement consumption)	-0.0025	0.0009	-2.892	0.0038
X_3 (CED cases)	0.0231	0.0037	6.197	<0.0001

Both variables in the final model were statistically significant at $\alpha = 0.05$. The estimated negative binomial regression model is:

$$\hat{\mu}_i = \exp(2.1273 - 0.0025X_{i2} + 0.0231X_{i3}).$$

The simultaneous test using the likelihood ratio test yielded a G-statistic of 42.989 ($p < 0.001$), confirming that the model with predictors X_2 and X_3 provides a significantly better fit than a null model with only an intercept. The goodness-of-fit test, based on the deviance statistic (value = 2.00) which is less than the chi-square table value ($\chi^2(9,0.05) = 16.919$), indicated that the model fits the data adequately. This low deviance value, close to its degrees of freedom, is a strong indicator that the negative binomial model has successfully accounted for the overdispersion present in the raw data, making it a reliable tool for inference.

3.3. Discussion

The results of this study demonstrate that the negative binomial regression model is a suitable tool for analyzing overdispersed count data, such as the number of LBW cases across sub-districts in Kolaka Regency. This finding aligns with previous methodological studies that advocate for its use in the presence of overdispersion to obtain more efficient and reliable estimates compared to standard Poisson regression (Rahayu, 2020; Efendi & Yotenka, 2021; Fatmala et al., 2024). By correctly modeling the error structure, this approach provides greater confidence that the significant relationships identified are not statistical artifacts.

The analysis identified two key factors significantly associated with LBW incidence. First, the number of pregnant women who consumed 90 iron supplement tablets (X_2) had a negative coefficient (-0.0025). At the aggregate level, this translates to an Incidence Rate Ratio (IRR) of exp(-0.0025) = 0.9975. While the effect per individual woman appears small, the public health impact is substantial when scaled across a population. For example, if the number of women completing the full iron supplementation regimen increases by 10 in a sub-district, the expected number of LBW cases is reduced by approximately 2.5% ($1-0.9975^{10}$), holding other factors constant. This finding is consistent with previous

research by Pradana (2024), who found that inadequate iron supplementation (<90 tablets) significantly increases the risk of LBW. It also corroborates the broader understanding that adequate iron and folic acid intake during pregnancy is crucial for preventing maternal anemia and supporting optimal fetal growth, thereby reducing the likelihood of LBW (Nabila & Andriani, 2023). The protective effect of comprehensive antenatal care, of which iron supplementation is a key component, is further echoed in Pertiwi's (2023) findings on the negative association between K4 coverage and LBW. From a policy perspective, this result strongly supports programs aimed at not just distributing iron supplements but ensuring adherence and completion of the full 90-tablet regimen.

Second, the number of pregnant women with chronic energy deficiency (X_3) showed a significant positive coefficient (0.0231). The corresponding IRR is exp(0.0231) = 1.023. This indicates that at the sub-district level, for every additional pregnant woman with CED in a sub-district, the expected number of LBW cases multiplies by a factor of 1.023, holding iron supplementation constant. The effect size for CED is nearly an order of magnitude larger than the protective effect of iron supplementation, highlighting the profound impact of chronic undernutrition. This result strongly reinforces the findings of Prihandani et al. (2022) and Maolida et al. (2024), which established a significant link between maternal CED and LBW. CED reflects a chronic state of undernutrition, meaning the mother lacks adequate energy and nutrient reserves to support her own health and the full growth and development of the fetus (Deswita et al., 2024). This nutritional deficit directly contributes to intrauterine growth restriction, a primary pathway to LBW, especially in full-term infants. The consistency of this finding across different regions and study designs underscores that addressing maternal malnutrition is a fundamental priority for LBW prevention. This calls for integrated interventions that go beyond pregnancy, such as improving adolescent girls' nutrition, delaying age at first pregnancy, and providing food supplementation programs for undernourished pregnant women.

The critical role of maternal nutritional status as a determinant of birth outcomes is further contextualized by understanding the broader socioeconomic and demographic factors that shape chronic energy deficiency among women of reproductive age. A comprehensive study in Bangladesh by Dey et al. (2024), which analyzed data from the Bangladesh Demographic and Health Survey 2017-18, found that the nutritional status of ever-married women, measured by BMI, was significantly influenced by a complex interplay of factors. Their multinomial logistic regression analysis revealed that women residing in urban areas, those belonging to richer wealth quintiles, and those with higher education were significantly more likely to be overweight or obese. Conversely, and most relevant to our findings on CED, the study identified that women in rural areas, those with lower educational attainment (both for themselves and their husbands), and those from poorer households had a higher prevalence of underweight. This reinforces the notion that CED is not merely a medical condition but a manifestation of underlying social and economic inequalities (Dey et al., 2024). Therefore, effective prevention of LBW in Kolaka Regency requires not only clinical interventions like iron supplementation but also upstream strategies that address women's education, poverty alleviation, and equitable access to nutritional resources, as these are the root causes of chronic undernutrition identified in similar South Asian contexts.

The novelty of this study lies not only in its methodological approach but also in its empirical contribution to the understanding of LBW determinants at a localized, regency level in a resource-limited setting. While global and national studies have established broad risk factors, this research provides a context-specific quantification of their effects, revealing that the coverage of a specific, high-impact intervention (complete iron supplementation) and a direct measure of chronic malnutrition (CED) are more powerful predictors of LBW incidence than a composite indicator of antenatal care coverage (K4). This nuanced finding has direct implications for targeted public health resource allocation in Kolaka Regency.

A recent pooled analysis from Nepal by Khanal et al. (2024) further strengthens our findings. Their study, which analyzed nationally representative data from the Nepal Demographic and Health Surveys (2016 and 2022), demonstrated that both ANC visits and iron-folic acid supplementation were independently and significantly associated with LBW. Specifically, mothers who attended less than four ANC visits (AOR: 1.49; 95% CI: 1.14-1.95) and those who consumed iron-folic acid for ≤90 days (AOR: 1.43; 95% CI: 1.11-1.84) had a higher likelihood of delivering LBW infants. Notably, their study also revealed a synergistic effect: mothers who had less than four ANC visits AND consumed iron-folic acid for ≤90 days had the highest likelihood of LBW (AOR: 1.88; 95% CI: 1.35-2.60) compared to those who met both recommendations. This finding from Nepal aligns with our results from Kolaka, reinforcing that the combination of inadequate ANC and incomplete iron supplementation exacerbates the risk of poor birth outcomes.

Interestingly, the percentage of K4 coverage (X_1) was not a significant predictor in the multivariate model. This does not negate the importance of antenatal care, as its key components, such as iron supplementation, were captured by X_2. It suggests that in the context of Kolaka Regency in 2024, the quantity of specific, high-impact interventions (like iron

supplementation and nutritional status) might be more directly predictive of LBW rates than the overall coverage of K4 visits, which could vary in quality. However, the ecological nature of this study, where data are aggregated at the sub-district level, means these findings represent associations at the aggregate level and cannot be directly inferred as causal at the individual level (ecological fallacy). This is the primary limitation of this study; the relationships observed at group level may not hold for individuals within those groups. Future research could utilize individual-level data or multilevel modeling to bridge this gap and confirm these findings. Despite this limitation, the study provides robust, population-level evidence that can guide strategic health planning in Kolaka and similar settings.

The findings of this study should be interpreted with caution due to the small sample size (n = 12 sub-districts). Although statistical significance was achieved, a sample of this size increases the risk of overfitting, reduces statistical power, and may produce less precise parameter estimates. Furthermore, the ecological study design prevents causal inference at the individual level (ecological fallacy). Therefore, the generalizability of the model is limited to the context of Kolaka Regency in 2024. Future studies with larger sample sizes and individual-level data are needed to validate these findings.

4. Conclusion

This study successfully applied negative binomial regression to model the overdispersed count data of LBW cases in Kolaka Regency in 2024. The analysis identified two significant determinants of LBW incidence at the sub-district level. Specifically, the number of pregnant women consuming 90 iron supplement tablets had a negative effect (β_2 = -0.0025; IRR = 0.9975), indicating that each additional woman completing the full regimen reduces the expected number of LBW cases by approximately 0.25%. Conversely, the number of pregnant women with chronic energy deficiency (CED) had a positive effect (β_3 = 0.0231; IRR = 1.023), meaning that each additional CED case increases the expected number of LBW cases by approximately 2.3%. These quantitative findings underscore the need for public health interventions in Kolaka Regency to prioritize improving adherence to complete iron supplementation and implementing programs for early detection and management of CED among pregnant women. Future research should incorporate larger sample sizes and individual-level data to enhance generalizability.

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