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Socioeconomic Determinants of Undernutrition Among Children Under Five: Evidence from Southeast Sulawesi, Indonesia

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Abstract. *Southeast Sulawesi has a high prevalence of undernutrition in children under five (27.7%) in 2024. Socio-economic factors such as poverty and maternal education are suspected to influence this condition. This study aims to analyze the influence of poverty levels and maternal education (Mean Years of Schooling/MYS) on the prevalence of child undernutrition in 17 districts/cities in Southeast Sulawesi. Secondary data from the Central Statistics Agency (BPS) in 2024 were used, with 17 observations. Analysis was conducted using Negative Binomial Regression to address overdispersion. Independent variables were the percentage of the poor population and the MYS of women. The Negative Binomial Regression model was confirmed as the best fit. Maternal education had a significant negative effect on undernutrition cases (IRR = 0.688; p=0.012). The poverty level also showed a significant negative relationship (IRR = 0.863; p=0.034). Maternal education plays an important role in reducing the risk of undernutrition. The negative relationship between poverty and undernutrition indicates the presence of specific factors or intervention programs in Southeast Sulawesi that require further investigation.*

Keywords: *Socioeconomic Determinants; Undernutrition; Children Under Five*

1. Introduction

Adequate nutritional intake during early life, particularly in children under five years of age, constitutes a fundamental foundation for human capital development, as it significantly influences physical growth, cognitive development, and long-term health outcomes. Nevertheless, in Indonesia, the nutritional status of children under five remains a serious public health concern. According to the national survey report, the prevalence of stunting among children under five in Indonesia reached 21.6% in 2022 (Indonesia Ministry of Health, 2022). Although this figure indicates improvement compared to previous years, the prevalence of undernutrition among children remains relatively high and requires sustained intervention.

At the regional level, Southeast Sulawesi Province is among the provinces with a relatively high prevalence of undernourished children under five. Data indicate that the prevalence of stunting in Southeast Sulawesi reached 27.7%, exceeding the national average. Several reports have even identified Southeast Sulawesi as a priority area for intervention due to substantial disparities in undernutrition prevalence across districts/cities (Indonesia Ministry of Health, 2022). This condition underscores that undernutrition among children under five in Southeast Sulawesi represents a critical issue warranting further investigation.

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Furthermore, multiple determinants influence the nutritional status of children under five, encompassing not only immediate factors such as dietary intake and infectious diseases, but also underlying socio-economic conditions. Poverty levels and parental education are frequently cited as fundamental (aggregate) determinants that shape caregiving quality and household food access. Data from the Central Statistics Agency indicate considerable variation in poverty rates and Mean Years of Schooling (MYS) across districts in Southeast Sulawesi (Central Statistics Agency (BPS), 2024)

This study aims to analyze the influence of socio-economic factors, particularly poverty rates and maternal Mean Years of Schooling (MYS), on the prevalence of undernutrition across 17 districts/cities in Southeast Sulawesi Province. Considering that undernutrition case data constitute discrete (count) data and often exhibit substantial variance (overdispersion), the analysis employs a Generalized Linear Model (GLM) approach to obtain precise and unbiased parameter estimates. This study contributes novel evidence by examining district-level socioeconomic determinants of undernutrition in Southeast Sulawesi using a Negative Binomial Regression approach. To our knowledge, few studies in Indonesia have applied this method to assess the relationship between maternal education, poverty, and undernutrition at the regional level.

2. Methods

This study utilized secondary data derived from official 2024 statistics published by Central Statistics Agency (BPS) of Southeast Sulawesi Province. The population comprised all administrative districts and municipalities within Southeast Sulawesi Province. The study sample consisted of 17 observational units, including 15 districts and 2 municipalities. The unit of analysis was the district/municipality level, with variables including the number of undernourished infant cases, the percentage of the population living in poverty as an indicator of poverty, and female Mean Years of Schooling (MYS) as an indicator of maternal education. Undernutrition was defined as the total number of children under five years of age in each district/city who were classified as undernourished (underweight) according to the nutritional status records reported in 2024. This variable served as the dependent variable in the analysis. While poor population is the percentage of the total population in each district living below the official poverty line established by the Central Statistics Agency in 2024. This variable was used as an indicator of the socioeconomic condition of the district. MYS is the average number of years of formal education completed by women aged 25 years and above in each district/city. This variable was used as a proxy for maternal educational attainment.

Data analysis was conducted using R Studio software with a Negative Binomial Regression model. Negative Binomial Regression is a non-linear regression model derived from the Poisson–Gamma mixture distribution as an application of the Generalized Linear Model (GLM). This model describes the relationship between the dependent variable and the independent variables under investigation. The negative binomial approach is commonly employed to address overdispersion in Poisson regression models

The number of undernutrition cases was defined as the response variable, while the percentage of the population living in poverty and Mean Years of Schooling (MYS) were defined as independent variables.

3. Results and Discussion

3.1 Descriptive Analysis

The data used in this study comprised 17 districts/municipalities. Descriptive analysis was conducted to provide an overview of the distribution of the response variable (undernutrition) and the predictor variables (percentage of population living in poverty and Mean Years of Schooling/MYS).

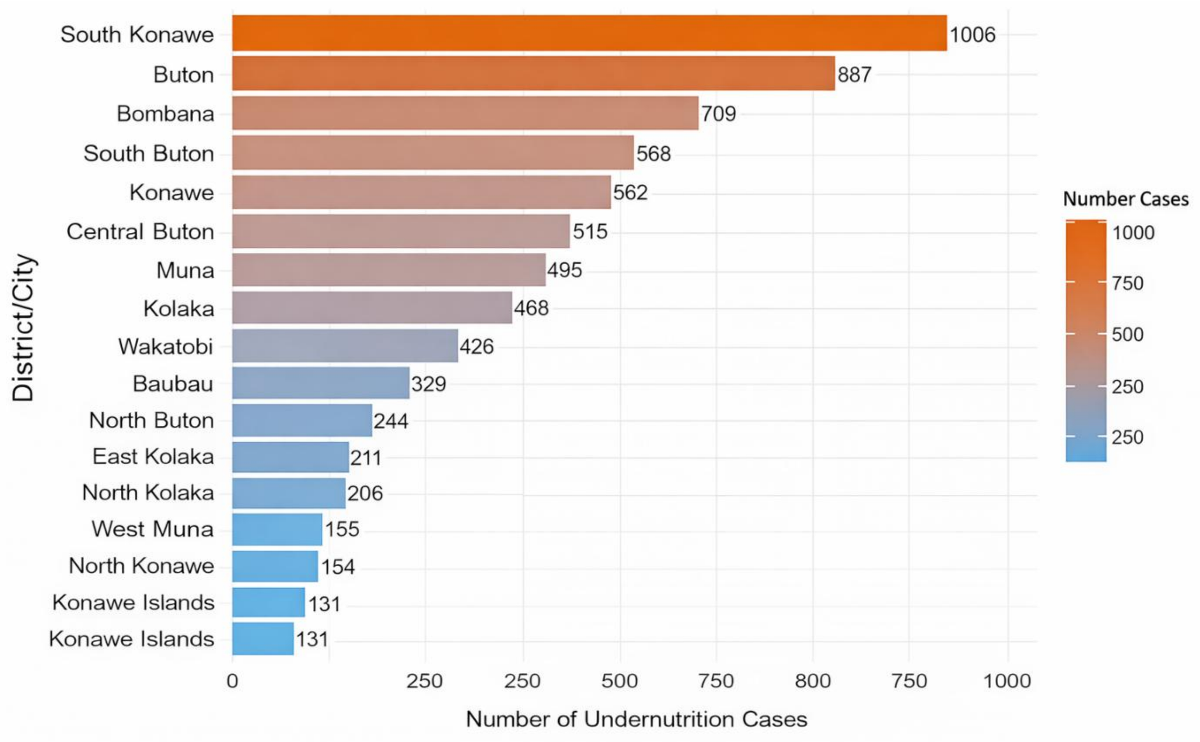

Figure 1. Distribution of Undernutrition Cases by District in Southeast Sulawesi Province

Based on Figure 1, the highest number of cases was observed in South Konawe District, with 1,006 cases, whereas the lowest number of cases was reported in Konawe Islands District. A substantial range in the distribution of cases across districts is evident.

Table 1. Descriptive Statistics of Y, X1, dan X2

Variables	Minimum	Maximum	Mean	Variance
Undernutrition cases (Y)	131.0	1006	433.8	66663.94
Poor Population (X1)	4.23	15.54	12.50	-
Mean Years of Schooling (X2)	6.37	12.13	8.695	-

Based on Table 1, the mean number of undernutrition cases was 433.8, accompanied by substantial variability. This is indicated by the variance value (66663.94), which is considerably higher than the mean. The variance-to-mean ratio (dispersion index) reached 153.69. In count data analysis, a condition in which the variance exceeds the mean (Var(Y) > E(Y)) indicates the presence of overdispersion.

The lowest percentage of the population living in poverty was recorded at 4.23% (Kendari Municipality), while the highest was 15.54% (Konawe Islands District), with an overall mean of 12.5%. Regarding Mean Years of Schooling (MYS), the lowest value was 6.37 years (Central Buton District) and the highest was 12.13 years (Kendari Municipality), with a provincial average of 8.7 years.

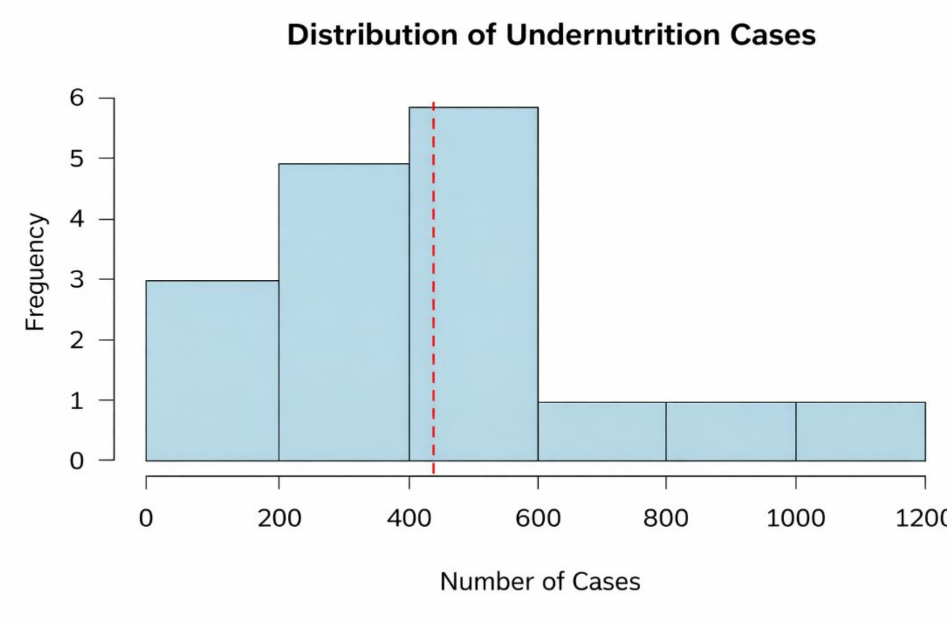

Figure 2. Histogram of variable response

Based on Figure 2, the majority of districts/municipalities recorded undernutrition cases within the range of 200 to 600 cases, as indicated by the tallest bars in the histogram corresponding to this interval. Only a small number of areas reported very low case counts (below 200) or very high case counts (above 800). The distribution of undernutrition cases is therefore uneven, with the largest concentration in the mid-range category and several districts exhibiting exceptionally high case counts that may be considered outliers.

Subsequently, the linear relationships among variables were examined using Pearson's correlation analysis, as presented below.

Table 2. Pearson's correlation analysis result

Variables	**Undernutrition cases**	**Poor Population**	**Mean Years of Schooling**
Undernutrition cases	1.000	-0.056	-0.271
Poor Population	-0.056	1.000	-0.776
Average Years of Schooling	-0.271	-0.776	1.000

Based on Table 2, a relatively strong correlation is observed between the percentage of the population living in poverty and Mean Years of Schooling (MYS), with a correlation coefficient of r = −0.776. The magnitude of this correlation between the independent variables indicates the need for further assessment of multicollinearity using the Variance Inflation Factor (VIF) prior to estimating the regression model.

3.2 Multicollinearity Analysis

Multicollinearity testing was conducted to ensure the absence of very strong correlations or perfect linear relationships among the independent (predictor) variables in the regression model. The presence of multicollinearity may inflate the variance of regression coefficients, thereby reducing the precision and reliability of parameter estimates. In this study, multicollinearity was assessed using the Variance Inflation Factor (VIF) method.

The test was conducted based on the VIF value criterion with the following hypotheses. H_0: There is a multicollinearity problem among the independent variables. H_1: There is no multicollinearity problem among the independent variables. A significance level of 0.05 was applied in this study. (H_0) was rejected if the VIF value exceeded 10, indicating that multicollinearity was not present among the independent variables.

Table 3. Result of Multicolinearity Test

Independent Variables	VIF Value	Tolerance Limit	conclusion
Poor Population (X1)	2.544	10	No Multicolinearity
Mean Years of Schooling (X2)	2.544	10	No Multicolinearity

Based on Table 3, the VIF values for the percentage of the population living in poverty and Mean Years of Schooling (MYS) are identical, at 2.544. This value remains well below the commonly accepted threshold of 10. Although the correlation matrix indicates a relatively strong negative correlation between poverty and MYS (r = −0.776), the VIF results confirm that this correlation is not sufficiently high to induce serious multicollinearity issues within the model.

Accordingly, H_0 was not rejected, indicating that no serious multicollinearity was detected. Therefore, both independent variables are deemed appropriate for simultaneous inclusion in the Poisson regression modeling framework.

3.3 Poisson Regression Modeling

Given that the response variable consists of discrete (count) data, the initial analytical approach employed a Generalized Linear Model (GLM) with a Poisson distribution. Poisson regression is the standard modeling approach for count data. Evaluation of the dispersion assumption in the Poisson model subsequently determines whether an alternative specification, such as the Negative Binomial model, is required (Agresti, 2013).

The parameter estimates and goodness-of-fit statistics from the Poisson model are presented in the following table:

Table 4. Poisson Regression Result

Parameter	Coefficiant	Std.Error	Z Value	P-value
Intercept	10.733	0.192	56.03	<2e-16***
Poor Population (X1)	-0.139	0.007	-20.31	<2e-16***
Mean Years of Schooling (X2)	-0.340	0.014	-24.64	<2e-16***
Indicator of Goodness of Fit				
Null Deviance	2382.9			
Residual Deviance	1778.5			
Degress of Freedom	14			
AIC	1916			
Dispersion ration	127.038			

The p-values presented in Table 4 indicate that all predictor variables have a statistically significant effect on the response variable. However, the validity of the Poisson regression model critically depends on the equidispersion assumption, whereby the variance of the response variable must be equal to its mean.

The dispersion statistic was calculated at 127.038, a value substantially greater than 1, which represents the expected dispersion under a standard Poisson model. This finding provides strong evidence of extreme overdispersion in the data. Consequently, the Poisson regression model is deemed inappropriate for this dataset. The analysis should therefore proceed using a method capable of accommodating overdispersion, namely the Negative Binomial Regression model.

3.4 Negative Binomial Regression Modeling

The parameter estimation results for the Negative Binomial Regression model are presented in the following table:

Table 5. Negative Binomial Regression Modeling result

Parameter	Estimate	Pr(>|z|)
Intercept	11.128	5.95e-08***
Poor Population (X1)	-0.148	0.0340
Mean Years of Schooling (X2)	-0.374	0.0123
Indicator of Goodness of Fit		
Null Deviance	23.618	
Residual Deviance	17.686	
Degress of Freedom	14	
AIC	234.78	
Dispersion ration	1.263	

Based on Table 5, the resulting model equation is:

$$\ln(\hat{\mu}) = 11.128 - 0.148X_1 - 0.374X_2$$

The model demonstrates an improvement, as reflected by the relatively low AIC value (234.78). In addition, the dispersion ratio of 1.263 indicates that the variance-to-mean relationship of the response variable is approximately equal, suggesting that the overdispersion issue has been substantially addressed in the Negative Binomial Regression model.

3.5 Best Model Evaluation

Based on the results of the Poisson regression and Negative Binomial Regression modeling, a comparative analysis was conducted to evaluate the performance of both models:

Table 6. Comparison of Goodness-of-Fit Indicators between Poisson Regression and Negative Binomial Regression

Model	AIC	Dispersion Ration
Poisson	1916	127.038
Negative Binomial	234.78	1.263

The Negative Binomial model produced an AIC value of 234.78, substantially lower than the Poisson model's AIC of 1916. This marked reduction indicates that the Negative Binomial model provides a considerably better fit to the data.

Moreover, the dispersion ratio for the Negative Binomial model was close to 1 (1.263), which is far more appropriate compared to the Poisson model's dispersion value of 127.038.

Based on thee findings, it can be concluded that the Negative Binomial Regression model demonstrates superior performance and is more appropriate for use in this study.

3.6 Partial Significance Test of the Negative Binomial Regression Model

(i). Hypotheses

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

$H_1: \beta_j \neq 0$(The independent variable affects the dependent variable.)

(ii). Reject H_0if the p-value < 0.05.

(iii). Decision

Table 7. Test of the Negative Binomial Regression Model

Parameter	Z value	Pr(>|z|)
Intercept	5.420	5.95e-08***
Poor Population (X1)	-2.120	0.0340*
Mean Years of Schooling (X2)	-2.504	0.0123*

(iv). Conclusion

Partial hypothesis testing was conducted using the Wald test. The results indicate that the percentage of the population living in poverty yielded a z-statistic of −2.120 with a corresponding p-value of 0.034. Meanwhile, Mean Years of Schooling (MYS) produced a z-statistic of −2.503 with a p-value of 0.012.

Given that the p-values for both predictor variables are smaller than the significance level ($\alpha = 0.05$), the null hypothesis (H_0) is rejected. This finding suggests that, on a partial basis, both poverty level and educational attainment (MYS) have a statistically significant effect on the prevalence of undernourished infants.

3.7 Interpretation of the Negative Binomial Regression Results

The effect of the percentage of the population living in poverty (X_1) and Mean Years of Schooling (X_2) on the response variable—the number of undernutrition cases (Y)—can be interpreted using the following Incident Rate Ratios (IRR):

Table 8. Incident Rate Ratios (IRR) from the Negative Binomial Regression Model

Parameter	p - value	IRR
Intercept	5.95e-08	-
Poor Population (X1)	0.034	0.863
Mean Years of Schooling (X2)	-0.012	0.688

Mean Years of Schooling (MYS) has a statistically significant negative effect on the number of undernutrition cases (p = 0.0123). The IRR value of 0.688 indicates that for every one-year increase in Mean Years of Schooling, the risk of undernutrition is estimated to decrease by 31.2% (1 − 0.688), assuming the poverty level remains constant.

The percentage of the population living in poverty also shows a statistically significant effect with a negative coefficient (p = 0.0340). The IRR value of 0.863 suggests that for every 1% increase in the proportion of the population living in poverty, the number of undernutrition cases is estimated to decrease by 13.7%.

3.7 Subsection Discussion

This study found that maternal education, measured by Mean Years of Schooling (MYS), had a statistically significant negative association with the number of undernutrition cases among children under five. The IRR value of 0.688 indicates that every additional year of maternal education was associated with a 31.2% reduction in the expected number of undernutrition cases, after controlling for poverty level. This finding is consistent with recent evidence showing that maternal education is one of the strongest social determinants of child nutritional status (Victora et al., 2021).

Higher educational attainment among mothers may improve nutritional outcomes through several pathways. Educated mothers are more likely to understand child feeding recommendations, recognize early signs of illness, utilize preventive health services, and adopt appropriate hygiene and sanitation practices. A recent systematic review and meta-analysis found that higher maternal education was significantly associated with better weight-for-age and height-for-age outcomes, particularly in low- and middle-income countries

(Rezaeizadeh et al., 2024). In addition, children of mothers with low educational attainment had significantly higher odds of stunting compared with children of educated mothers(Amaha & Woldeamanuel, 2021).

Recent studies continue to confirm the importance of maternal education in reducing undernutrition. A multi-country analysis across 68 developing countries reported that each additional year of maternal schooling significantly reduced the probability of child stunting and undernutrition, highlighting the important role of maternal education in improving child nutritional outcomes (Le & Nguyen, 2020). Another study in South Asia demonstrated that maternal education remained a stronger predictor of child nutrition than household income after adjustment for other socioeconomic variables (Torlesse & Aguayo, 2018)

The findings of the present study therefore reinforce the argument that investments in female education may generate long-term nutritional benefits across generations. Improving access to secondary education for girls, particularly in rural and disadvantaged districts of Southeast Sulawesi, should be prioritized as part of a long-term strategy to reduce child undernutrition.

Unexpectedly, this study identified a significant negative association between poverty level and the number of undernutrition cases. The IRR value of 0.863 suggests that a 1% increase in the proportion of the population living in poverty was associated with a 13.7% decrease in the expected number of undernutrition cases. This finding differs from the conventional literature, which generally reports that poverty increases the risk of child undernutrition because poor households have limited access to food, health services, clean water, and sanitation (Nandy et al., 2005).

Several contextual explanations may account for this counterintuitive result. First, districts with higher poverty rates in Southeast Sulawesi may have been prioritized for social assistance and nutrition intervention programs. In Indonesia, districts with higher poverty and undernutrition burdens often receive more intensive support through food supplementation, conditional cash transfers, village-level nutrition programs, and integrated stunting reduction interventions. Consequently, children in poorer districts may have benefited disproportionately from these targeted programs (Mulyaningsih et al., 2021). Likewise, recent findings from low- and middle-income countries indicate that conditional cash transfer programs and food subsidy schemes are associated with improved dietary intake and lower rates of child undernutrition among poor households (Hartarto et al., 2023) (Bhutta et al., 2013).

Second, the present analysis was conducted at the district level rather than at the household level. Relationships observed across districts do not necessarily reflect conditions at the household level. Poorer districts may simultaneously receive stronger nutrition and social protection programs, while poor households within those districts remain vulnerable to undernutrition. In addition, unmeasured contextual factors—such as food security, sanitation, health service access, urbanization, and local government spending—may confound the observed association (Khan, 2018).

Other studies have similarly shown that district-level poverty is not always positively associated with child malnutrition after accounting for government intervention and public service coverage. An ecological analysis from India reported that the relationship between poverty and child malnutrition was substantially attenuated in districts with better maternal education, sanitation, and access to health services, indicating that stronger public services and social programs can mitigate the adverse effects of poverty on child nutrition (Khan, 2018). Furthermore, recent global estimates suggest that inequalities in child growth failure are increasingly shaped by access to services and regional policy responses rather than by poverty alone (Kinyoki et al., 2020) (UNICEF, WHO, 2025).

Therefore, the negative association identified in this study should not be interpreted as evidence that poverty protects against undernutrition. Rather, it likely reflects the influence of unmeasured contextual factors and intervention programs operating in high-poverty districts.

The use of Negative Binomial Regression was appropriate because the undernutrition count data exhibited substantial overdispersion. The variance of the response variable was much larger than its mean, indicating that the assumptions of Poisson regression were violated. The Negative Binomial model substantially improved the model fit, as indicated by the reduction in AIC and the dispersion ratio approaching 1.

Negative Binomial models are widely recommended when the variance exceeds the mean, as they provide more reliable parameter estimates and standard errors than Poisson regression. Recent methodological studies recommend Negative Binomial Regression for overdispersed public health count data because it provides more accurate standard errors and more reliable parameter estimates than Poisson regression (Hilbe, 2012) . Compared with the Poisson model, the negative binomial approach is better able to accommodate heterogeneity across districts and reduce the risk of biased inference in ecological health studies (Hilbe, 2012). The final model in this study therefore offers a more robust basis for interpreting the effects of poverty and maternal education on child undernutrition in Southeast Sulawesi.

The findings of this study indicate that strategies to reduce undernutrition in Southeast Sulawesi should not focus solely on economic growth, but also on improving maternal education and strengthening nutrition-sensitive social protection programs. Policies aimed at increasing girls' educational attainment may have long-term effects on reducing child undernutrition. At the same time, poverty-targeted interventions should continue to be strengthened and evaluated to ensure that the most vulnerable households are effectively reached.

Future research should incorporate additional variables, such as household food security, sanitation, health service coverage, and maternal employment, in order to better explain the complex relationship between poverty and undernutrition. Longitudinal and household-level studies are also needed to clarify causal pathways and avoid the limitations of ecological analysis.

3.8 Study limitations

This study has several limitations. First, the analysis was conducted at the district level using only 17 observations, which may limit statistical power and introduce ecological fallacy. Second, the use of secondary data prevented inclusion of important household-level variables such as food security, sanitation, and maternal employment. Third, the cross-sectional design precludes causal inference. Therefore, the findings should be interpreted cautiously.

Conclusions

This study demonstrates that maternal education and poverty level are significantly associated with the prevalence of undernutrition among children under five in Southeast Sulawesi. Maternal Mean Years of Schooling (MYS) showed a significant protective effect, indicating that higher maternal education contributes to lower undernutrition rates. This finding emphasizes the importance of improving female educational attainment as part of long-term strategies to enhance child nutrition.

In contrast, the negative association observed between poverty and undernutrition differs from the conventional expectation that poorer areas experience worse nutritional outcomes. This pattern may reflect the influence of targeted social protection and nutrition intervention programs that are more intensively implemented in high-poverty districts. However, because the analysis was conducted at the district level, the findings should be interpreted cautiously and may not necessarily represent household-level relationships.

Methodologically, the Negative Binomial Regression model proved more appropriate than Poisson regression because it effectively addressed the substantial overdispersion in the data. Overall, the findings suggest that reducing undernutrition in Southeast Sulawesi requires a multisectoral approach that combines improvements in maternal education with more effective and equitable nutrition-sensitive interventions in vulnerable communities.

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Conflicts of Interest

The authors declare no conflict of interest.

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