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THE INFLUENCE OF MODERATING FACTORS IN STUNTING: LOGISTIC PATH ANALYSIS OF ORDINAL DATA

Shalsa Amalia Yulianto [1*], Solimun[2], Achmad Efendi[3], Adji Achmad Rinaldo Fernandes[4]

[1,2,3,4]*Statistics, Faculty of Mathematics and Natural Sciences, Universitas Brawijaya*
Jln. Veteran Malang, Ketawanggede, Lowokwaru, Malang, Jawa Timur, 65145, Indonesia

*Corresponding author's e-mail: * **shalsaamaliayulianto@gmail.com***

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ABSTRACT

Logistic path analysis is used to analyze direct and indirect causal relationships between exogenous-endogenous variables with categorical data types. This study aims to apply logistic path analysis to ordinal categorical data and model the relationship between exogenous variables that affect nutritional status and physical status (stunting) in toddlers in Sumberputih Village, Wajak District. The data used is secondary data obtained from the results of filling out questionnaires in Sumberputih Village at the time of data collection in 2022-2023. The sample used in the study was 100 housewives who had toddlers. The sampling technique used was judgment sampling. However, the study only selected the variables of Birth Weight, Dietary Habits, Nutritional Status, and Physical Status (Stunting). The result of this study is that the variable of Birth Weight has a significant direct effect on Nutritional Status. The variable of Birth Weight has an indirect effect, and the total effect on Physical Status (Stunting) mediated by Nutritional Status is not significant. Meanwhile, the Diet variable has a significant direct effect on Physical Status. In addition, the Socioeconomic Condition variable can moderate the relationship between the Birth Weight variable and Physical Status. The diversity of data that can be explained by the model is 80.36%, while the rest is explained by other variables outside the model by 19.64%.

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1. INTRODUCTION

Stunting is one of the most serious health problems in Indonesia, especially in children. Based on data from the National Nutritional Status Survey (SSGI) in 2022, the prevalence of stunting in Indonesia was 21.6%. This number decreased compared to the previous year, which was 24.4%. Although declining, this figure is still high, considering that the stunting prevalence target in 2024 is 14.6% and the WHO standard is below 20% [1]. Stunting occurs due to a lack of adequate nutrition during critical periods of child growth, especially during the first 1,000 days of life. Children who are stunted tend to have shorter height than their peers and delayed cognitive development. The main factors leading to stunting are poverty, limited access to nutritious food, and lack of knowledge about the importance of nutrition during pregnancy and early childhood [2]. The government, through various nutrition, health, and sanitation programs, is trying to address the stunting problem, but many challenges remain. One of the main challenges is the uneven distribution of programs and assistance in remote areas, as well as a lack of commitment and understanding of the importance of preventing stunting from an early age [3]. In addition, social and economic factors can strengthen the relationship between several factors causing stunting and the prevalence of stunting. Therefore, social and economic factors serve as moderating variables [4].

The Ministry of State Secretariat of the Republic of Indonesia 2024 [5] stated that the target of reducing the prevalence of stunting in Indonesia is aligned with the global target, namely the World Health Assembly (WHA) target to reduce the prevalence of stunting by 40% by 2025 from 2013 conditions. In addition, the Sustainable Development Goals (SDGs) target is to eliminate all forms of malnutrition by 2030 [6]. For this reason, efforts are needed to accelerate the reduction of stunting from the current condition so that the prevalence of stunting in toddlers drops to 19.4% by 2024 [7]. Stunting in Indonesia is still a significant problem that requires serious attention from various parties. Currently, the Indonesian government has established a stunting management program as one of the national priorities [8]. This program requires an integrated approach to effectively reduce and suppress the increase in the number of stunting cases. According to data shown by Databook Katadata in 2021, Indonesia is the second country with the highest prevalence of stunted children in Southeast Asia [9]. The problem of stunting has an impact on the quality of human resources in both the short and long term. According to the Ministry of PPN [10], the short-term effects of stunting cases will cause failure in the growth of children or toddlers, experiencing obstacles in the cognitive and motor development of children, as well as low height and other health problems. One of the regions in East Java that pioneered the acceleration of the stunting prevention program is Malang District. Bappeda Malang District designated 32 villages as priority villages for accelerating stunting prevention in 2021, one of which is Sumberputih Village, Wajak District. In this village, approximately 63% of the community was reported to be less concerned about stunting prevention [11]. Moreover, in 2023, Wajak District experienced a surge in stunting, reaching 400 cases, significantly higher than in other villages. Factors that influence the prevalence of stunting levels with the moderation of social and economic factors can be identified through ordinal logistic path analysis with a moderating variable approach.

Path analysis is a development analysis of multiple regression analysis with the aim of examining the relationship between variables in the form of cause and effect [12]. According to Valenzuela & Bachmann [13], path analysis is a statistical technique used to analyze causal relationships between exogenous and observed endogenous variables, including direct and indirect relationships. The use of path analysis requires attention to the data measurement scale that will be used in the study. According to Hidayat et al. [14], data based on the measuring scale can be divided into nominal, ordinal, interval, and ratio data. Interval and ratio scales are categorized as quantitative (metric) data. While the nominal and ordinal data scales are qualitative (nonmetric), the data must be converted into numerical data by scoring or can be done with a logistic model. This aims to make it easier to find information related to solutions and problems that exist. To analyze the relationship between categorical response variables and numerical or categorical predictor variables, logistic regression analysis can be used. Therefore, logistic path analysis was developed to determine the direct and indirect effects on categorical responses. To complement the influence of exogenous variables on endogenous variables in path analysis, moderating variables can be incorporated. According to Solimun et al. [15], moderating variables can be variables that strengthen or weaken the influence of exogenous variables on endogenous variables. According to Menufandu et al. [16], the mediation moderation model can be referred to as moderated mediation. This means path analysis can be used in various fields of life, one of them being the health sector [17].

To deal with these problems, one of the statistical methods that can be applied is using logistic path analysis. Previous research by Picauly et al. [18] used path analysis for preventing stunting. It was found that both specific & sensitive intervention programs had an influence in accelerating the decline in stunting prevalence (higher score on Z-Score). The positive influence of the food access variable on nutritional intake. The results of the path analysis test showed that sensitive intervention program variables have a positive effect on food access variables and environmental variables (environmental sanitation) such as the habit of open defecation and healthcare. There was a significant relationship between disease history, environment, and intake to Height for Age score. However, the study did not use categorical variables on the endogenous variable, and in this study, it was not sought to determine how big the chance was that a child would fall into the stunting, normal, or tall category. Nuryasmin's research [19] says that categorical path analysis can be used to determine the direct and indirect effects on binary categorical data, where in the case of this study, the effect of job stress on job satisfaction and employee performance was seen. The results showed that there was a relationship between work stress variables on job satisfaction and employee performance had a significant effect. However, the study did not involve moderating variables to see how influential moderating variables were in strengthening or weakening the relationship between exogenous variables and endogenous variables [20]. Therefore, in this study, categorical path analysis was conducted with moderation variables on ordinal data to determine the variables that affect stunting.

2. RESEARCH METHODS

The data used in this study is secondary data obtained from the results of questionnaire responses in Sumberputih Village during the data collection period in 2022-2023. The population of this study consists of all households in Sumberputih Village with toddlers. The sampling technique used is judgment sampling, where the selected sample consists of mothers with toddlers. The sample size was determined to be 100 respondents, all of whom were used as the sample in this study. The determination of the sample size is based on Hair et al. [21], which states that when a model equation contains ≤ 7 variables, at least 100 samples are required. This study, however, utilizes five variables.

The variables used in this study are Birth Weight (X_1) and Dietary Habits (X_2) as predictor variables, and Socioeconomic Condition (X_3) as a moderating variable. The dependent variables are Nutritional Status (Y_1) and Physical Status (Y_2), both of which are ordinal scale variables with 3 categories as the limitation of this study. The Nutritional Status variable (Y_1) consists of category 1 (Deficient), category 2 (Fair), and category 3 (Good), while the Physical Status variable (Y_2) consists of category 1 (Stunting), category 2 (Normal), and category 3 (High). Data with these variables will be analyzed using ordinal logistic path analysis with a moderating variable approach. The steps of this research can be seen more concisely in Figure 1.

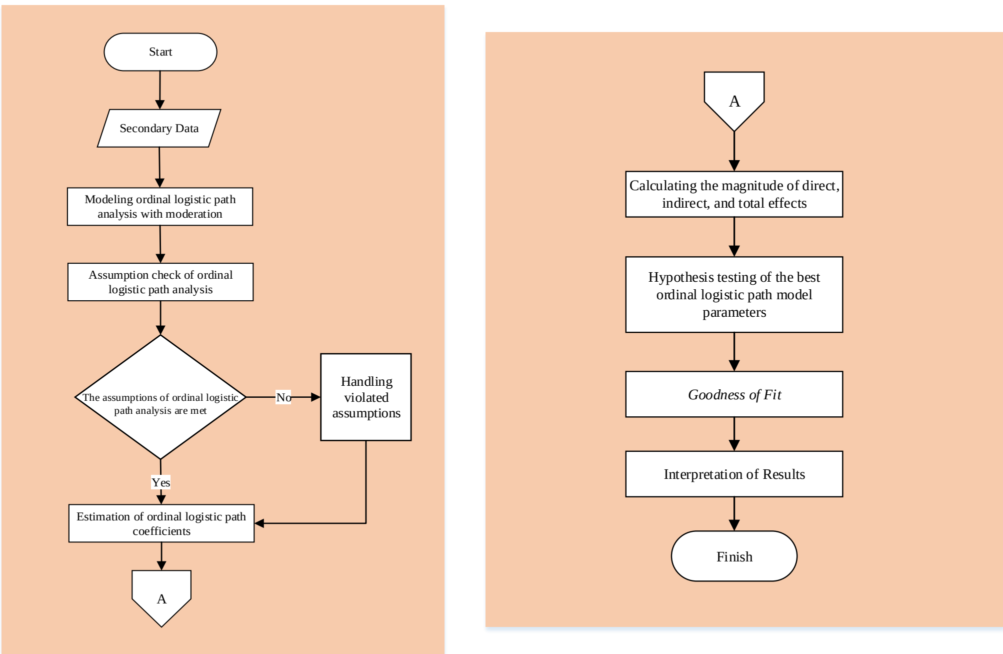

Figure 1. Research Flow Chart

2.1 Ordinal Logistic Path Analysis

Fahrmeir and Gerhard [22] state if there is a response variable with k ordinal scale categories with k more than two, Ordinal Logistic Regression (OLR) is used, and this model is based on cumulative probability. Response variable with k categories can be viewed as k classes of unobserved continuous variables. The form of the relationship between the observable response variable and the unobservable response variable can be explained as follows:

$$y_i = \begin{cases} 1 & for \quad u_i \le \theta_1 \\ 2 & for \quad \theta_1 < u_i \le \theta_2 \\ \vdots & \\ k-1 & for \quad \theta_{k-2} < u_i \le \theta_{k-1} \\ k & for \quad \theta_{k-1} < u_i \end{cases}$$
$$\text{with assumptions } u_i = -(\beta_1 x_{i1} + \dots + \beta_p x_{ip}) + v_i \tag{1}$$

where:

u_i	:	unobserved response variable
y_i	:	observed response variable
$x_{1i}, \dots, x_{pi}$	:	explanatory variable
v_i	:	residual
$\beta_1, \dots, \beta_p$	:	coefficient of the explanatory variable
$\theta_1, \dots, \theta_{k-1}$	:	limit for the unobserved response variable
p	:	number of explanatory variables ($q = 1, 2, \dots, p$)
k	:	number of response variable categories ($j = 1, 2, \dots, k$)

So it can be explained that ordinal response variables can also be classes of unobserved continuous response variables that have constraints with unknown values. The cumulative probability for the response variable is:

$$\begin{aligned} P(y_i \le j) &= P(u_i \le \theta_j) \\ &= P\left((\beta_1 x_{i1} + \dots + \beta_p x_{ip}) + v_i \le \theta_j\right) \\ &= P(v_i \le \theta_j + \beta_1 x_{i1} + \dots + \beta_p x_{ip}) \\ &= F(v_i) \end{aligned} \tag{2}$$

Because u_i is assumed to be logistic distributed with a cumulative function:

$$\begin{aligned} F(v_i) &= \frac{1}{1 + \exp(-v_i)} \\ &= \frac{\exp(v_i)}{1 + \exp(v_i)} \end{aligned} \tag{3}$$

then the cumulative probability of the response variable **Equation (3)** can be written as:

$$P(y_i \le j) = \frac{exp(\theta_j + \beta_1 x_{i1} + \dots + \beta_p x_{ip})}{1 + exp(\theta_j + \beta_1 x_{i1} + \dots + \beta_p x_{ip})} \tag{4}$$

2.2 Moderation Variable

According to Solimun [23], the moderating variable is a variable that strengthens or weakens the effect of the predictor or explanatory variable (independent) on the response variable or dependent variable (dependent). One of the important characteristics of the moderating variable is that it is not influenced by the explanatory variable. In general, the effect of moderating variables is indicated by the multiplication between the independent variable indicator and the moderating variable indicator.

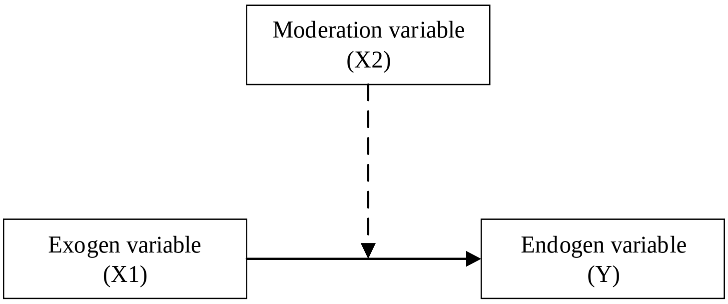

Figure 2. Moderation Model

Variable categories can be identified in the following example. X is the explanatory variable, Y is the dependent variable, and M is the moderator variable, the regression equation that can be constructed is as follows:

1) Without involving moderating variables

$$Y_i = \beta_{10} + \beta_{11}X_i + \varepsilon_i \tag{5}$$

2) Involving moderating variables

$$Y_i = \beta_{20} + \beta_{21}X_1 + \beta_{22}X_2 + \beta_{22}X_1 * X_2 + \varepsilon_i \tag{6}$$

Based on **Equation (5)** and **Equation (6),** the cumulative probability ordinal logistic path analysis equation with moderation in this research can be written in **Equation (7)** to **Equation (8)** below:

For Nutritional Status variables (X_1, X_2moderation by X_3 to Y_1)

$$\pi_1(x) = \frac{exp(\beta_{011} + \beta_{11}X_{1i} + \beta_{21}X_{2i} + \beta_{31}X_{3_i} + \beta_{41}X_{1i} * X_{3i} + \beta_{51}X_{2i} * X_{3i})}{1 + exp(\beta_{011} + \beta_{11}X_{1i} + \beta_{21}X_{2i} + \beta_{31}X_{3_i} + \beta_{41}X_{1i} * X_{3i} + \beta_{51}X_{2i} * X_{3i})} \tag{7}$$

$$\pi_2(x) = \frac{exp(\beta_{012} + \beta_{11}X_{1i} + \beta_{21}X_{2i} + \beta_{31}X_{3i} + \beta_{41}X_{1i} * X_{3i} + \beta_{51}X_{2i} * X_{3i})}{1 + exp(\beta_{012} + \beta_{11}X_{1i} + \beta_{21}X_{2i} + \beta_{31}X_{3i} + \beta_{41}X_{1i} * X_{3i} + \beta_{51}X_{2i} * X_{3i})} \tag{8}$$

For Physical Status variables : (X_1, X_2, Y_1 moderation by X_3 to Y_2)

$$\pi_1(x) = \frac{exp(\beta_{021} + \beta_{12}X_{1i} + \beta_{22}X_{2i} + \beta_{32}Y_{1i} + \beta_{42}X_{3i} + \beta_{52}X_{1i} * X_{3i} + \beta_{62}X_{2i} * X_{3i} + \beta_{72}Y_{1i} * X_{3i})}{1 + exp(\beta_{021} + \beta_{12}X_{1i} + \beta_{22}X_{2i} + \beta_{32}Y_{1i} + \beta_{42}X_{3i} + \beta_{52}X_{1i} * X_{3i} + \beta_{62}X_{2i} * X_{3i} + \beta_{72}Y_{1i} * X_{3i})} \tag{9}$$

$$\pi_2(x) = \frac{exp(\beta_{022} + \beta_{12}X_{1i} + \beta_{22}X_{2i} + \beta_{32}Y_{1i} + \beta_{42}X_{3i} + \beta_{52}X_{1i} * X_{3i} + \beta_{62}X_{2i} * X_{3i} + \beta_{72}Y_{1i} * X_{3i})}{1 + exp(\beta_{022} + \beta_{12}X_{1i} + \beta_{22}X_{2i} + \beta_{32}Y_{1i} + \beta_{42}X_{3i} + \beta_{52}X_{1i} * X_{3i} + \beta_{62}X_{2i} * X_{3i} + \beta_{72}Y_{1i} * X_{3i})} \tag{10}$$

With:

$\boldsymbol{X_1}$: Birth Weight

$\boldsymbol{X_2}$: Dietary Habits

$\boldsymbol{X_3}$: Socioeconomic Condition

$\boldsymbol{Y_1}$: Nutritional Status

$\boldsymbol{Y_2}$: Physical Status

2.3 Parameter Estimation of Ordinal Logistic Path Analysis

One method that can be used to estimate logistic regression parameters is logistic Maximum Likelihood Estimation (MLE) [24]. The iteration method used is the Newton-Raphson iteration method. The parameter estimation method in ordinal logistic path regression uses the Maximum Likelihood Estimation (MLE) method. If the response variable y ~ Ordinal ($y_1, y_2, \ldots, y_k$; n ; $\pi_1, \pi_2, \ldots, \pi_k$) then the likelihood function for observation y is:

$$\ell(\theta, \beta) = \prod_{i=1}^{n} (\pi_1(X))^{y_{1i}} (\pi_2(X))^{y_{2i}} \ldots \pi_k(X))^{y_{ki}} \tag{11}$$

Where :

y_j vector of response variables for j categories ($j = 1, \ldots, k$)

n total observations $= y_{1i} + y_{2i} + \ldots + y_{ki}$

$\pi_j(X)$ probability vector for y_j

2.4 Moderating Variable Analysis (Interaction Variable)

There are moderating variables that have numeric variables, and some are categorical [15]. To analyze moderating variables that have numeric data types, a moderation regression approach is used. Moderation regression analysis involves moderating variables in building the relationship model. Moderating variables act as explanatory variables and add their interaction to the direct relationship between exogenous and endogenous variables.

2.5 Ordinal Logistic Path Analysis Model Fit Test

To find the appropriate model, it is necessary to test its suitability. Testing the suitability of the model is done partially using the Wald test with the following explanation.

1) Partial Testing (Wald Test)

The hypothesis used in this partial test is:

$H_0: \beta_i = 0$, vs
$H_1: \beta_i \neq 0 \ (i = 1,2,3, \ldots, p)$
The test statistics used are:

$$W_i = \frac{\hat{\beta}}{SE(\hat{\beta}_i)} \tag{12}$$

where:
$\hat{\beta}$: estimator β_i
$SE(\hat{\beta}_i)$: standard error estimator of β_i

To check the size of the logistic path analysis model, you can use the odds ratio as the path coefficient. The odds ratio is an indicator of the tendency for something to happen or not happen. The odds of an event are defined as the probability of an outcome occurring divided by the probability of an event not occurring. *Odds* (ψ) defined as:

$$odds = \frac{\pi_i}{1 - \pi_i}$$

$$\varphi = \frac{oddsA}{oddsB} = \left[\frac{\frac{\pi_A}{(1-\pi_A)}}{\frac{\pi_B}{(1-\pi_B)}}\right] \tag{13}$$

where :
π_i : the probability of success (occurrence of event $Y = 1$)
$1 - \pi_i$: the probability of failure (occurrence of event $Y = 0$).

2.6 Goodness of Fit Path Logistic Analysis

Testing goodness of fit in path analysis using the coefficient of total determination. The total coefficient of determination is the total diversity that can be explained by the model. The coefficient of total determination can be calculated using the following formula:

$$R^2{}_{Total} = 1 - P^2{}_{e_1} P^2{}_{e_2} \ldots P^2{}_{e_M} \tag{14}$$

While the effect of residuals can be calculated using **Equation (15)**:

$$P^2{}_{e_M} = 1 - R^2{}_{MF_m} \tag{15}$$

The coefficient of determination can be calculated by **Equation (16)**:

$$R^2{}_{MF_m} = 1 - \frac{l_m}{l_{0m}} \tag{16}$$

With :

$R^2{}_{Total}$: coefficient of total determination

$P^2{}_{e_M}$: the square of the effect of the i-th model leftover ($i = 1,2,\ldots,M$)

$R^2{}_{MF_m}$: coefficient of determination of the i-th model ($i = 1,2,\ldots,M$)

l_m : loglikelihood of the i-th model ($i = 1,2,\ldots,M$)

l_{0m} : null loglikelihood of the i-th model ($i = 1,2,\ldots,M$)

2.7 Birth Weight

Low Birth Weight (LBW) is a condition in which a baby is born weighing less than 2,500 grams. LBW has been shown to be one of the main risk factors influencing the incidence of stunting in children under five years of age. Abuya et al. [25] stated that the risk of stunting in infants with LBW was 1.18 times higher compared to infants born with normal weight. The multivariate analysis shows that infants born with LBW were 1.74 times more likely to be stunted (95% CI = 1.38–2.19) than those born with normal weight.

2.8 Dietary Habit

Dietary habits play a crucial role in the prevention and management of stunting among children. Adequate intake of essential nutrients like dairy products, nuts, vegetables, and legumes is crucial. Maternal nutrition, exclusive breastfeeding, and socioeconomic status also significantly influence the risk of stunting. Interventions aimed at improving dietary diversity and healthcare access can effectively reduce the incidence of stunting among children [26].

2.9 Nutritional Status

Toddler nutritional consumption is used to provide an overview of dietary patterns and nutrition that can affect stunting. The determination of the three categories of less, enough, and more is as follows in Table 1 [27].

Table 1. Toddler Nutrition Category

Criteria	Category
$\boldsymbol{X \leq \frac{2a+b}{3}}$	Not Enough
$\boldsymbol{\frac{2a+b}{3} < X < \frac{a+2b}{3}}$	Enough
$\boldsymbol{X \geq \frac{a+2b}{3}}$	More than Enough

With:
a : Minimum value of the total possible score
b : Maximum value of the total possible score

2.10 Physical Status

According to Ginting et al. [28], the causes of stunting include poor parenting, lack of pregnancy check-ups, obstacles to access to clean water, and infectious diseases suffered by children. In addition, other factors come from social, economic, cultural, and political factors. Standard deviation (SD) is the standard deviation value set by Permenkes RI Number 2, 2020.

Table 2. Toddler Nutrition Category

Criteria	Category
$X \leq -2SD$	Stunting
$-2SD < X < 2SD$	Normal
$X \geq 2SD$	High

2.11 Socioeconomic Condition

Economic conditions, especially household income, are one of the factors that can influence the incidence of stunting in toddlers [29]. Families with lower economic status often struggle to provide adequate nutrition and healthcare, increasing the risk of stunting among children. Children from low-income families are more susceptible to stunting due to limited access to nutritious food and health services [30]. Economic disparities directly impact nutritional outcomes [31]. Addressing these economic challenges is essential for reducing stunting prevalence and promoting healthy development in children.

3. RESULTS AND DISCUSSION

3.1 Parameter Estimation

Parameter estimation in ordinal logistic path analysis is carried out using the Maximum Likelihood Estimation (MLE) method. The results of parameter estimation using Software R can be seen in Table 3.

Table 3. Path Coefficient

Variable Relationship	Path Coefficient	Test Statistics t-value	Odds Ratio
$X_1 \to Y_1$	0.458	2.999	1.580
$X_2 \to Y_1$	0.576	2.733	1.778
$X_3 \to Y_1$	0.050	3.823	1.051
$X_1 \to Y_2$	0.054	-2.301	1.055
$X_2 \to Y_2$	-1.233	-2.980	0.291
$X_3 \to Y_2$	0.259	3.388	1.296
$Y_1 \to Y_2$	1.054	1.378	2.869
	1.206	2.196	3.340

Description:
Y1 →1= Deficient; 2 = Fair; 3 = Good
Y2 →1= Stunting; 2 = Normal; 3 = High

- Model 1

Model 1 is a logistic regression model of the effect of the ratio-scale exogenous variable Birth Weight (X_1) and Dietary Habits (X_2) on ratio scale Nutritional Status (Y_1) on an ordinal scale. Parameter estimation with the MLE method gets the value $\beta_{0\,2|1} = -5.072$, $\beta_{0\,2|3} = -3.453$, $\beta_{X_1Y_1} = 0.458$ and $\beta_{X_2Y_1} = 0{,}576$, $\beta_{X_3Y_1} = 0{,}050$, $\beta_{X_3X_1Y_1} = 0.001$, $\beta_{X_3X_2Y_1} = 0.058$. The logistic model is as follows:

$$\pi_1(x) = \frac{exp(-5.072 + 0.458X_1 + 0.576X_2 + 0.050X_3 + 0.001X_3 * X_1 + 0.058X_3 * X_2)}{1 + exp(-5.072 + 0.458X_1 + 0.576X_2 + 0.050X_3 + 0.001X_3 * X_1 + 0.058X_3 * X_2)}$$

$$\pi_1(x) = \frac{exp(-3.453 + 0.458X_1 + 0.576X_2 + 0.050X_3 + 0.001X_3 * X_1 + 0.058X_3 * X_2)}{1 + exp(-3.453 + 0.458X_1 + 0.576X_2 + 0.050X_3 + 0.001X_3 * X_1 + 0.058X_3 * X_2)}$$

- Model 2

Model 2 is a logistic regression model of the effect of the exogenous variable Birth Weight (X_1), Dietary Habits (X_2) on ratio scale, and Nutritional Status (Y_1) on an ordinal scale on the Physical Status (Y_2) on an ordinal scale. Parameter estimation with the MLE method obtained the value of

$\beta_{0\ 2|1} = -1.346$, $\beta_{0\ 2|3} = -1.526$, $\beta_{X_1Y_2} = 0.054$, $\beta_{X_2Y_2} = -1.233$, $\beta_{Y_1Y_{2|1}} = 1.054$, $\beta_{Y_1Y_{2|2}} = 1.206$, $\beta_{X_3Y_2} = 0.259$, $\beta_{X_3X_1Y_1Y_2} = 0.324$, $\beta_{X_3X_2Y_1Y_2} = 0.083$, $\beta_{X_3Y_1Y_{2|1}} = 0.043$, and $\beta_{X_3Y_1Y_{2|2}} = 0.026$. The logistic model is as follows:

$$\pi_1(x) = \frac{exp(-1.346 + 0.054X_1 - 1.233X_2 + 1.054Y_1 + 0{,}259X_3 + 0.324X_3 * X_1 + 0.083X_3 * X_2 + 0.043X_3 * Y_1)}{1 + exp(-1.346 + 0.054X_1 - 1.233X_2 + 1.054Y_1 + 0{,}259X_3 + 0.324X_3 * X_1 + 0.083X_3 * X_2 + 0.043X_3 * Y_1)}$$

$$\pi_1(x) = \frac{exp(-1.526 + 0.054X_1 - 1.233X_2 + 1.054Y_1 + 0{,}259X_3 + 0.324X_3 * X_1 + 0.083X_3 * X_2 + 0.043X_3 * Y_1)}{1 + exp(-1.526 + 0.054X_1 - 1.233X_2 + 1.054Y_1 + 0{,}259X_3 + 0.324X_3 * X_1 + 0.083X_3 * X_2 + 0.043X_3 * Y_1)}$$

3.1.1 Partial Test

The Wald Test was conducted at a significance level (α) of 0.05 to determine whether the independent variables have a significant effect on the dependent variables. The results are summarized in the following table to provide readers with a clear understanding of the significance of each variable's impact:

Table 4. Partial Test

Model	Variables	*p*-Value	Conclusion
1	Birth Weight (X_1)	0.002*	Birth Weight (X_1) has a significant effect on Nutritional Status (Y_1).
1	Dietary Habits (X_2)	0.006*	Dietary Habits (X_2) have a significant effect on Nutritional Status (Y_1).
1	Socioeconomic Condition (X_3)	< 0.001*	Socioeconomic Condition (X_3) has a significant effect on Nutritional Status (Y_1).
2	Birth Weight (X_1)	0.020*	Birth Weight (X_1) has a significant effect on Physical Status (Y_2).
2	Dietary Habits (X_2)	< 0.001*	Dietary Habits (X_2) have a significant effect on Physical Status (Y_2).
2	Socioeconomic Condition (X_3)	< 0.001*	Socioeconomic Condition (X_3) has a significant effect on Physical Status (Y_2).
2	Nutritional Status (Y_1) (stunting)	0.168^{ts}	Nutritional Status (Y_1) (stunting) does not have a significant effect on Physical Status (Y_2).
2	Nutritional Status (Y_1) (normal)	< 0.028*	Nutritional Status (Y_1) (normal) has a significant effect on Physical Status (Y_2).

*: Significant, ^{ts}: Not Significant

3.1.2 Odds Ratio

The magnitude of the effect of ordinal logistic path analysis can be seen through the Odds Ratio (OR) value obtained by the equation $\pi\ (x) = exp\ (\beta_{X_iY_i})$. Birth Weight ($X_1$) has a positive effect on nutritional status, where an increase in birth weight increases the odds of a child having a better Nutritional Status (Y_1) by 1.580 times. Dietary Habits (X_2) have a significant positive effect on Nutritional Status (Y_1), with an odds ratio of 1.778 times for improved nutritional status. However, strangely, better Dietary Habits were negatively associated with Physical Status (Y_2) with an odds ratio of 0.291, suggesting other factors affect physical growth despite adequate nutrition. Good Nutritional Status (Y_1) significantly increases the odds of better Physical Status (Y_2) by 2.869 times. This suggests that children with good nutritional status are much more likely not to be stunted and to have normal or above-normal height.

3.2 Goodness of Fit Ordinal Logistic Path Analysis

The coefficient of determination in ordinal logistic path analysis can be seen through the results of the McFadden R^2 value. The following is the total coefficient of determination from the ordinal logistic path analysis equation:

- Model 1

$$R^2_{MF_1} = 0.570$$

$$P^2_{e_1} = 1 - R^2_{MF_1} = 1 - 0.470 = 0.430$$

- Model 2

$$R^2_{MF_2} = 0.544$$

$$P^2_{e_2} = 1 - R^2_{MF_2} = 1 - 0.544 = 0.456$$

- Total coefficient of determination

$$R^2_{total} = 1 - P^2_{e_1} P^2_{e_2}$$

$$R^2_{total} = 1 - (0.430)(0.456) = 1 - 0.1964 = 0.8036$$

3.3 Identification of the Effect of Moderating Variables on Ordinal Logistic Path Analysis

Variables can be moderated or not by looking at the path coefficient on the significant interaction effect. Identifying the role of the moderating variable, namely the Socioeconomic Condition (X_3) whether it strengthens or weakens a relationship can be seen from the effect of interaction or multiplication between exogenous variables and Socioeconomic Condition (X_3) in influencing endogenous variables and the effect of exogenous variables in influencing endogenous variables. The results of identifying the role of moderating variables are shown in **Table 5.**

Table 5. Identification of the Effect of Moderating Variables

Relationship	Coefficient	T-statistic	p-value	Conclude
$X_1 \to Y_1$	0.458	2.999	0.002^{*}	No Moderation
$X_1X_3 \to Y_1$	0.001	1.780	0.074^{ts}	
$X_2 \to Y_1$	0.576	2.733	0.006^{*}	Moderation Strengthen
$X_2X_3 \to Y_1$	0.259	3.388	$< 0.001^{*}$	
$X_1 \to Y_2$	0.054	-2.301	0.020^{*}	No Moderation
$X_1X_3 \to Y_2$	0.083	1.709	0.087^{ts}	
$X_2 \to Y_2$	-1.233	-2.980	$< 0.001^{*}$	Moderation Strengthen
$X_2X_3 \to Y_2$	4.707	4.217	$< 0.001^{*}$	
$Y_1 \to Y_{2.1}$	1.054	1.378	0.168^{ts}	No Moderation
$Y_1X_3 \to Y_{2.1}$	0.081	1.726	0.084^{ts}	
$Y_1 \to Y_{2.2}$	1.206	2.196	$< 0.028^{*}$	No Moderation
$Y_1X_3 \to Y_{2.2}$	0.058	1.823	0.068^{ts}	

Note :
* : Significant when p-value < 0.05, ts : Not Significant when p-value > 0.05
α : 0.05

Based on **Table 5**, the Socioeconomic Condition (X_3) is a moderating variable that strengthens the Dietary Habits (X_2) relationship to the Nutritional Status (Y_1) and the Physical Status (Y_2). This is known based on the p-value $< \alpha(0.05)$ and based on the path coefficient value of the direct relationship, which is negative and the interaction is positive. So it shows that the presence of socioeconomic will strengthen the relationship between Dietary Habits (X_2) to Nutritional Status (Y_1) and the Physical Status (Y_2). Where this means that when someone has a higher socioeconomic level, it guarantees that high Dietary Habits (X_2) are reinforced by high socioeconomic conditions as well. The test result of the moderating variable Socioeconomic Condition (X_3) for the effect of Nutritional Status (Y_1) to Physical Status (Y_2) high category compare with normal high ($Y_{2.1}$) has p-value of 0.084 and in the high category of normal toddlers compared to stunting ($Y_{2.2}$) has p-value of 0.068, so a decision can be made to accept H_0. With a real level of 5%, it can be concluded Socioeconomic Condition (X_3) variable does not significantly moderate the relationship between Nutritional Status (Y_1) to Physical Status (Y_2) In both conditions.

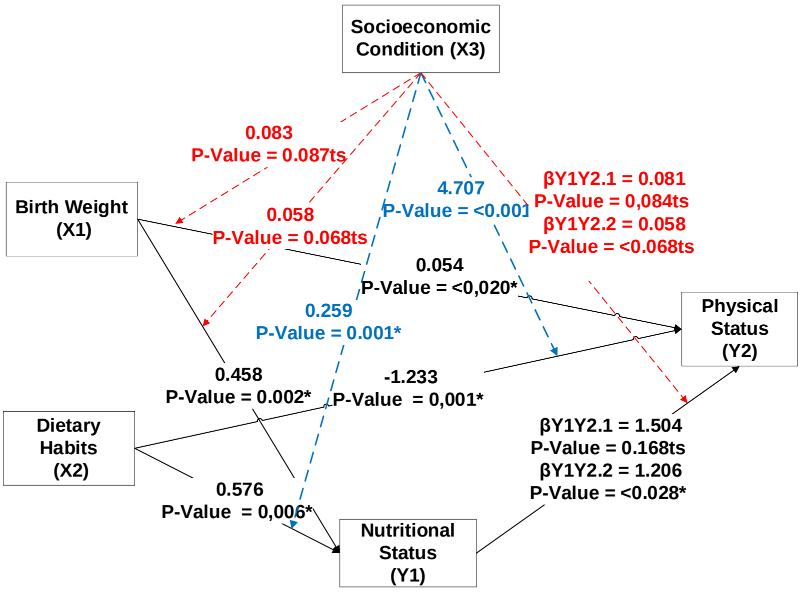

Figure 3. Path Coefficient Diagram with Moderating Variable

Note :
Blue Line : Significant
Red Line : Not Significant

Based on the **Figure 3**, Dietary Habits (X_2) may have a more direct or stronger influence on Nutritional Status (Y_1) and the Physical Status (Y_2), which means its influence is strong enough to be moderated by other variables, such as Socioeconomic Condition (X_3). Conversely, other variables may have an effect, but it is not strong enough to be significantly moderated by existing variables. Dietary Habits may be the variable most directly related to Nutritional Status, as eating habits largely determine a person's nutrient intake and health condition. This strong influence makes the moderation of other variables more visible, while variables such as birth weight or socioeconomic conditions may play more of an indirect role.

4. CONCLUSIONS

Based on the results of the analysis carried out in this research, several conclusions can be drawn.

1. Birth Weight (X_1) has a significant positive effect on nutritional status, where an increase in birth weight increases the odds of a child having a better Nutritional Status (Y_1) by 1.580 times. Dietary Habits (X_2) had a significant positive effect on Nutritional Status (Y_1), with an odds ratio of 1.778 times for improved nutritional status. However, strangely, better Dietary Habits were negatively associated with Physical Status (Y_2) with an odds ratio of 0.291, suggesting other factors affect physical growth despite adequate nutrition. The higher of Nutritional Status (Y_1) significantly increases the odds of better Physical Status (Y_2) by 2.869 times. This suggests that children with good nutritional status are much more likely not to be stunted and to have normal or above-normal height.
2. The Socioeconomic Condition variable becomes a moderating variable in the relationship between the Dietary Habits (X_2) variable and the Nutritional Status (Y_1), so the Physical Status (Y_2) too.

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