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DETERMINANTS MODELING OF UNDERNUTRITION IN TODDLERS IN ACEH PROVINCE: A PLS-SEM APPROACH

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ABSTRACT

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This study examines the escalating prevalence of underweight and wasting in Indonesia from 2019 to 2022. The prevalence of underweight has increased from 16.35% in 2019 to 17.1% in 2022 while wasting has increased from 7.4% to 7.7% during the same period. Aceh province faces a pressing issue of toddler malnutrition, ranking second with the highest prevalence of underweight (24.8%) and fourth highest in wasting prevalence (11.3%). According to the World Health Organization's malnutrition indicators classification, Aceh experiences notably high levels of underweight and very high levels of wasting. Employing Partial Least Squares Structural Equation Modeling (PLS-SEM) with data sourced from SSGI, publications from the Ministry of Health and BPS-Statistics Indonesia, and Aceh Provincial Food Agency, this research aims to model undernutritioned toddlers in Aceh Province. Findings reveal that undernutrition is directly affected by health access and food intake, with socioeconomic factors exerting an indirect effect. Notably, food intake emerges as the primary determinant of undernutrition.

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1. INTRODUCTION

Malnutrition in toddlers adversely affects children's health and development, such as stunted growth and muscle mass loss [1]. Generally, malnutrition in children leads to weakened immunity, making them more susceptible to illnesses. Therefore, reducing malnutrition cases is one of the key components of the Sustainable Development Goals (SDGs) [2].

The Indonesian Ministry of Health produces four malnutrition indicators through the Indonesian Nutrition Status Survey (SSGI): stunting, underweight, wasting, and overweight [3]. From 2019 to 2022, the prevalence of stunting has shown a significant decrease of 6.1 percent. However, it remains above the National Medium-Term Development Plan 2019-2024 (RPJMN) target of 14%. Similarly, the prevalence of overweight has decreased annually and is relatively small, below 5%. On the other hand, the prevalence of underweight and wasting increases. The prevalence of underweight has increased from 16.35% in 2019 to 17.1% in 2022. During the same period, the prevalence of wasting has also increased from 7.4% to 7.7%[3], [4], [5].

The results of the long-form Census of Population 2020 show that toddlers are the largest age group in terms of population in Aceh Province, totaling 490,875 individuals or 9.31% of the total population. Despite having a large number of toddlers, the under-five mortality rate in Aceh is also relatively high, at 22.88 deaths per 1,000 live births compared to the national rate of 19.83 deaths per 1,000 live births. One of the factors contributing to toddler mortality is malnutrition [6]. Malnutrition can exacerbate the risk of death, morbidity, and infection, as well as impair the mental, physical, and psychological development of children at an early age [1], [2].

The issue of toddler health in Aceh IS a serious problem that needs to be addressed urgently. In addition to toddler mortality, Aceh is also faced with the issue of undernutrition in toddlers, including stunting, wasting, and being underweight. Aceh ranks second in terms of the highest prevalence of underweight (24.8%) and fourth highest in the prevalence of wasting (11.3%) in Indonesia [3]. Based on the malnutrition indicators classification from the WHO[7], Aceh experiences a high prevalence of underweight and a very high prevalence of wasting.

Different interconnected components contribute to malnutrition in low-to-middle-income nations, including financial variables, child natural components, nourishment uncertainty, financial troubles, equipped strife, worldwide emergencies, nourishment emergencies, worldwide warming, movement, destitution, imbalance, and the spread of irresistible illnesses [8]. Malnutrition is synonymous with a deficiency in essential vitamins and minerals [9]. The study by [10] also indicates that diversity in animal protein consumption is associated with a lower risk of underweight and stunting in toddlers. The nutritional status of toddlers is also related to the household income level because income levels are associated with household food security, adequate healthcare services, and environmental health [11]. External factors, such as environmental factors, have a more significant effect on the nutritional status of toddlers than internal factors of toddlers themselves [12]. Health resources and environmental hygiene also play an important role in determining a child's nutritional status [6].

Direct factors determining a child's nutritional status include food intake and the diseases the child suffers from[13], [14]. Meanwhile, these factors are affected by socioeconomic conditions [14]. Similar findings are also found in other studies, where poverty factors reflected through socioeconomic variables such as per capita income, illiteracy rate, unemployment rate, and the proportion of GDP in the education sector affect undernutrition [6]. On the other hand, it is also mentioned that socioeconomic factors directly affect nutritional status [15]. Housing instability or low-quality housing may have a variety of negative repercussions on one's health and well-being, and housing is widely acknowledged as a crucial socioeconomic determinant of health [16]. A critical step in improving long-term social and economic well-being for those struggling with poverty is the provision of affordable housing [17].

The factors above are predominantly latent and cannot be directly measured. These factors necessitate construction from various indicators to construct latent variables. Hence, a method capable of accommodating the interrelationships among these latent variables is essential. Structural Equation Modeling (SEM) is a pertinent approach to interlinking unobserved variables (latent variables). It facilitates the modeling of intricate relationships between variables [18].

Previous research has utilized SEM to investigate malnutrition comprehensively. For example, one study explored the maternal effects and child factors contributing to stunting using Partial Least Squares SEM

(PLS-SEM) [19]. Similarly, another study identified the direct impact of environmental conditions, household food security, and maternal education on stunting through generalized SEM [20]. Additionally, SEM was employed to scrutinize the determinants of growth and nutrition in rural Chinese children [1]. This study will concentrate on the issue of undernutrition, explicitly focusing on underweight and wasting. Diverging from prior research practices, which typically utilize individuals as the unit of analysis, our methodology will broaden its scope by analyzing data at the district/city level. SEM and PLS-SEM are two methods to overcome the complexity models. SEM uses more observations than PLS-SEM. Because we only have 23 observations, we use the PLS-SEM.

This study will meticulously model and discern the factors influencing undernutrition in toddlers in Aceh Province, such as socioeconomic factors, health access, and food intake. By identifying the predominant factors contributing to undernutrition, this research enhances the efficacy of implemented programs to mitigate undernutrition in toddlers, thereby aiding governmental initiatives toward achieving improved nutritional outcomes.

2. RESEARCH METHODS

2.1 Data

The following are the variables utilized in this study.

Table 1. Research variables

Latent Variable	Code	Indicator Variable
Socioeconomic	X1	Average per capita expenditure (Rupiah/month)
	X2	Mean Year School (Year)
	X3	Percentage of Households with Per Capita Floor Area More than 10 m2 (percent)
Health Access	X4	Coverage of Pregnant Women Receiving Iron Supplement Tablets (Fe3) (percent)
	X5	Percentage of Households with Own Toilet Facilities (percent)
	X6	Coverage of Measles Immunization among Children Aged 0-23 Months (percent)
	X7	Percentage of Households with Handwashing Facilities (percent)
	X8	Coverage of Postpartum Women Receiving Vitamin A Supplementation (percent)
Food Intake	Y1	Animal Protein Consumption Adequacy Rate (percent)
	Y2	Fruit and Vegetable Consumption Adequacy Rate (percent)
	Y3	Score of Desirable Dietary Pattern (PPH/*Pola Pangan Harapan*)
Undernutrition	Y4	Prevalence of Underweight (percent)
	Y5	Prevalence of Wasting (percent)

The data utilized in this study, as shown in Table 1, are secondary data obtained from various sources, which consist of 23 regencies/cities in Aceh Province, including Y4 and Y5 [3] are indicators that describe undernutrition as an endogenous variable; X4, X6, X8 [4], X5 [21] and X7 [22] are indicators that describe health access as an exogenous variable; X1, X2, and X3 [21] are indicators that describe socioeconomic as an exogenous variable; and Y1, Y2 [21] and Y3 [23] are indicators that describe food intake as an endogenous variable.

Variable X1 is the proxy of average income per capita. Meanwhile, variable Y1 represents the actual proportion of animal food consumption to the percentage of recommended ideal animal food consumption (12% of total ideal energy). In comparison, Y2 is calculated from the actual proportion of fruit and vegetable consumption to the recommended ideal fruit and vegetable consumption (6% of total ideal energy). The ideal energy is the standard per capita daily nutritional consumption of 2,150 kcal/capita/day [24]. Meanwhile, Y3 is an indicator used to assess the quantity and composition of food. This score serves as an indicator of nutritional quality and dietary diversity in the community [25].

2.2 Undernutrition

In this study, undernutrition in toddlers is manifested through two indicators: underweight and wasting. Underweight describes toddlers with a weight-for-age (WAZ) z-score below minus two standard deviations (−2 SD) from the median of the reference population. On the other hand, wasting, also known as acute malnutrition, is a form of malnutrition that reflects a child's weight being too low for their height, characterized by a weight-for-height (WHZ) z-score less than -2 SD from the median of the reference population [26].

2.3 Structural Equation Model

A statistical method called structural equation modeling (SEM) allows for the simultaneous analysis of patterns of linear connections between indicator and latent variables [27]. Latent variables are essential constructs in a field of science, constructed based on theory or hypothesis [28]. Generally, there are two types of SEM, namely Covariance-based SEM (CB-SEM) and Partial Least Squares SEM (PLS-SEM) [29].

SEM comprises two primary components: the measurement model (outer model) and the structural model (inner model) [30]. The pattern of relationships between endogenous (dependent) latent variables and exogenous (independent) latent variables are illustrated by the structural model, as in Equation (1) below.

$$\boldsymbol{\eta} = \mathbf{B}\boldsymbol{\eta} + \boldsymbol{\Gamma}\boldsymbol{\xi} + \boldsymbol{\zeta} \tag{1}$$

The endogenous latent variable is represented by $\boldsymbol{\eta}$ in the form of an $m \times 1$ vector, while the exogenous latent variable represented by $\boldsymbol{\xi}$ in the form of an $n \times 1$ vector. $\mathbf{B}$ is a structural coefficient matrix sized $m \times m$ for the relationships among endogenous latent variables $\boldsymbol{\eta}$, while $\boldsymbol{\Gamma}$ is a structural coefficient matrix sized $m \times n$ for the relationships between endogenous latent variables and exogenous latent variables $\boldsymbol{\xi}$. Meanwhile, $\boldsymbol{\zeta}$ represents an error vector sized $m \times 1$, with an expected value of 0, and the error term $\boldsymbol{\zeta}$ is assumed to be uncorrelated. Furthermore, the measurement model is expressed in Equation (2) and Equation (3) as follows [31].

$$\mathbf{y} = \boldsymbol{\Lambda}_{\mathbf{y}}\boldsymbol{\eta} + \boldsymbol{\varepsilon} \tag{2}$$

$$\mathbf{x} = \boldsymbol{\Lambda}_{\mathbf{x}}\boldsymbol{\xi} + \boldsymbol{\delta} \tag{3}$$

With $\boldsymbol{y}$ sized $p \times 1$ and $\boldsymbol{x}$ sized $q \times 1$ representing vectors of observed variables, respectively. $\boldsymbol{\Lambda_y}$ with size p × m, and $\boldsymbol{\Lambda_x}$ with size $q \times n$ are coefficient matrices indicating the relationships from $\mathbf{y}$ to $\boldsymbol{\eta}$ and from $\boldsymbol{x}$ to $\boldsymbol{\xi}$. Meanwhile, $\boldsymbol{\varepsilon}$ is a vector with size $p \times 1$, and $\boldsymbol{\delta}$ with size $q \times 1$ represents the errors in the measurement of $\mathbf{y}$ and $\mathbf{x}$, respectively.

2.4 PLS-SEM

PLS-SEM is a variance-based structural equation modeling. The objective of PLS-SEM is to find predictive linear relationships among variables. Latent variables are defined as the sum of composite weights from their indicators. The PLS algorithm estimates component score outcomes for each latent variable based on indicator weights that maximize explained variance and minimize residual variance for the dependent variable.

The PLS-SEM algorithm explicitly computes case values (construct scores) for the latent variables. The algorithm estimates the latent variables as exact linear combinations of their empirical indicators [32] so that the resulting composites capture a significant portion of the variance of the exogenous constructs' indicators, which is valuable for predicting the endogenous constructs' indicators [33]. In a PLS path model, PLS-SEM utilizes these composites to represent the constructs, treating them as approximations of the conceptual variables being considered [34], [35], [36].

PLS-SEM algorithms as follows [37]:

Stage 1: Iterative process for estimating exogenous/endogenous latent variable scores (socioeconomic, health access, food intake, and undernutrition). The iteration starts from Step #3, repeat Step #1 to Step #3 until convergence is obtained.

#1: Inner weights (here obtained by using the factor weighting scheme)

$$v_{ji} = \begin{cases} \text{cov}(\eta_j, \xi_i) \text{ or } \text{cov}(\eta_j, \eta_i), & \text{if } \eta_j \text{ and } \xi_i \text{ are adjacent or if } \eta_j \text{ and } \eta_i \text{ are adjacent} \\ 0, & \text{otherwise} \end{cases}$$

#2a: Estimating approximations for the relationships in the structural model between endogenous latent variable scores (food intake)

$$\eta_j = \sum_i \gamma_i \xi_i$$

#2b: Estimating approximations for the relationships in the structural model between endogenous latent variable scores (undernutrition)

$$\eta_j = \sum_i (\beta_i \eta_i + \gamma_i \xi_i)$$

#3: Calculating latent variables scores based on the scores from Step 1 and the approximations for structural model relationships from Step 2

$$x_{k_j n} = \lambda_{k_j} \xi_{jn} + \delta_{k_j n}$$

$$y_{k_j n} = \lambda_{k_j} \eta_{jn} + \varepsilon_{k_j n}$$

Stage 2: Estimation of outer loadings and path coefficients.
Stage 3: Estimation of location parameters.

PLS-SEM is an alternative to CB-SEM when researchers have few observations. PLS-SEM can generate high statistical power even with a small sample size, where increasing the sample size enhances precision [18]. SEM using the PLS approach is highly robust as it does not necessitate fulfilling normality assumptions. PLS-SEM can only be applied to recursive (cause-effect) model forms and does not allow for non-recursive (reciprocity) relationships. The formula of PLS-SEM is the same as the formula of SEM as **Equation (1)**, **(2)**, and **(3)**.

2.5 Measurement Model Evaluation

2.5.1 Internal Consistency Reliability

Internal consistency reliability is the first criterion to be evaluated in the measurement model. This evaluation is conducted by considering the value of composite reliability. A latent variable is deemed consistent and reliable if it has a composite reliability value of more than 0.7 [27]. The composite reliability value is calculated using standardized outer loadings (l_i) and measurement errors (e_i). Composite reliability can be calculated using **Equation (4)** below.

$$\rho_c = \frac{\left(\sum_{i=1}^{M} l_i\right)^2}{\left(\sum_{i=1}^{M} l_i\right)^2 + \sum_{i=1}^{M} \mathrm{var}(e_i)} \tag{4}$$

2.5.2 Convergent Validity

Convergent validity measures the extent to which measurement indicators within the same latent variable are correlated. We use outer loading values and average variance extracted (AVE) for the measurement. A latent variable is considered valid if each of its indicators has an outer loading value greater than 0.5 and an AVE value greater than 0.5 [27]. AVE can be calculated using the **Equation (5)** below.

$$AVE = \frac{\sum_{i=1}^{M} l_i^2}{M} \tag{5}$$

2.5.3 Discriminant Validity

Discriminant validity is utilized to assess the extent to which each latent variable construct in the structural equation differs from one another. One indicator used to measure this is the heterotrait-monotrait ratio (HTMT). Heterotrait means average correlations between indicators from different constructs ($r_{ig,jh}$) while monotrait means average correlations between indicators from the same construct ($r_{ig,ih}$ or $r_{jg,jh}$). HTMT estimates the true correlation value between latent variables if they were measured perfectly. Each latent variable is considered distinct if it has an HTMT value of less than 0.9 [27]. Otherwise, some authors suggest a threshold of 0.85 [38], [39], [40]. HTMT value of the latent variable i and j with, respectively, K_i and K_j indicators can be calculated using the **Equation (6)** below.

$$HTMT_{ij} = \frac{\frac{1}{K_i K_j} \sum_{g=1}^{K_i} \sum_{h=1}^{K_j} r_{ig,jh}}{\sqrt{\frac{2}{K_i(K_i-1)} \sum_{g=1}^{K_i-1} \sum_{h=g+1}^{K_i} r_{ig,ih} \frac{2}{K_j(K_j-1)} \sum_{g=1}^{K_j-1} \sum_{h=g+1}^{K_j} r_{jg,jh}}} \tag{6}$$

2.6 Structural Model Evaluation

The evaluation of the structural model is conducted by considering the R^2 values. R^2 used to determine the extent to which exogenous latent variables can explain the variance of endogenous latent variables. Generally, R^2 values of 0.25, 0.50, and 0.75 for target constructs are considered weak, medium, and substantial, respectively [27]. The value of R^2 between 0.33 and 0.63 is moderate categorized [41].

2.7 Hypothesis Testing

Hypothesis testing is carried out using the resampling-bootstrapping method with 5000 bootstrap samples. The hypothesis is as follows:

H_0: The independent variable does not affect the dependent variable significantly.

H_1: The independent variable affects the dependent variable significantly.

Test statistics:

$$t_{statistic} = \frac{b_j}{se(b_j)} \tag{7}$$

In Equation (7), b_j represents the estimated value for B_j, $s(b_j)$ is the standard error for b_j. The null hypothesis is rejected if the t-statistic is greater than the t-distribution with 22 degrees of freedom at the significance level α = 0.05 or p-value < 0.05.

We used the SmartPLS 4.0.9.6 software with a student license to perform the latent variables and their indicators and evaluate the measurement and structural models.

3. RESULTS AND DISCUSSION

3.1 Measurement Model Evaluation

This study will evaluate or analyze the link between latent variables and their indicator. This measurement model study aims to ascertain the reliability and validity of indicators about a latent variable.

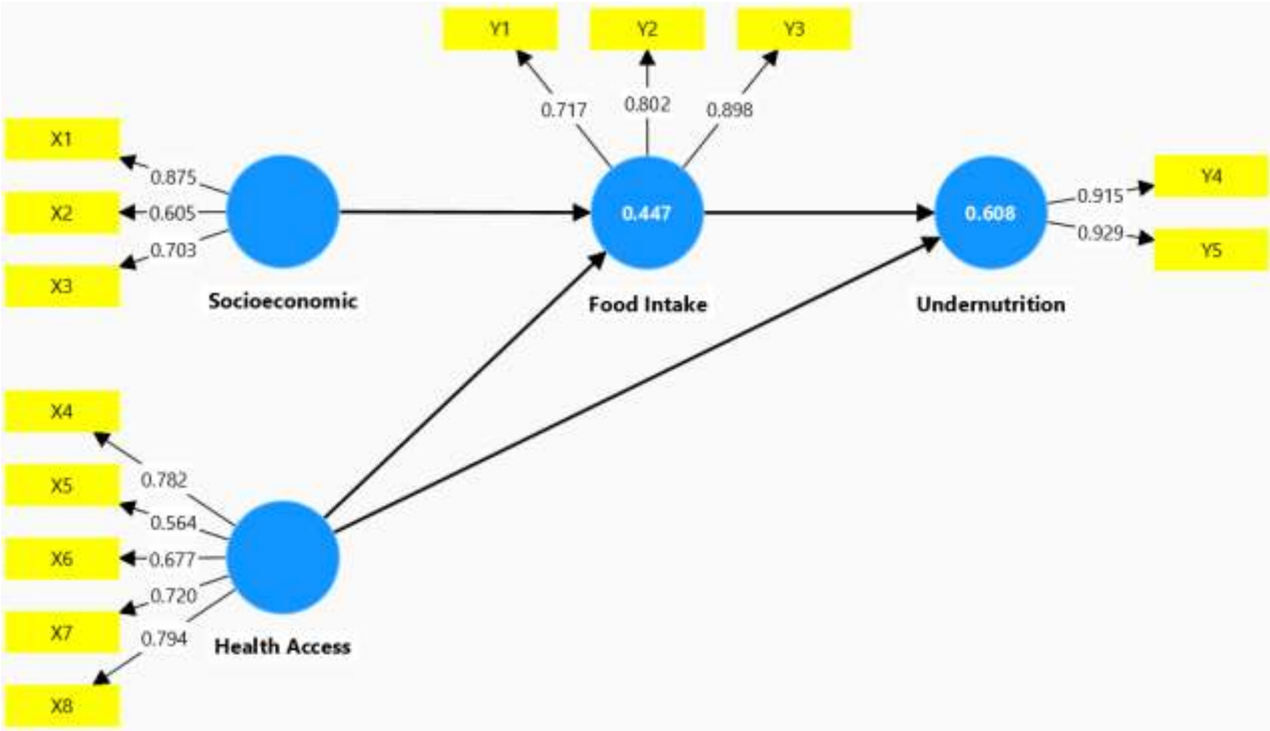

Figure 1. PLS-SEM undernutrition path diagram

Table 2. Measurement Model Evaluation

Latent Variable	Indicators	Composite Reliability	Outer Loading	AVE	Validity
Socioeconomic	X1	0.776	0.875	0.542	Valid
	X2		0.605		
	X3		0.703		
Health Access	X4	0.836	0.782	0.508	Valid
	X5		0.564		
	X6		0.677		
	X7		0.720		
	X8		0.794		
Food Intake	Y1	0.849	0.717	0.655	Valid
	Y2		0.802		
	Y3		0.898		
Undernutrition	Y4	0.919	0.915	0.850	Valid
	Y5		0.929		

Based on the evaluation of the measurement model presented in **Table 2**, each latent variable has a composite reliability value above 0.7. It indicates that the indicators used to manifest each latent variable are reliable and consistent. Regarding AVE values, all variables can also be considered valid, as, on average, each latent variable can explain the variance of its indicators.

The AVE value for the socioeconomic latent variable is 0.542, indicating that this latent variable can explain, on average, 54.2% of the variance of all its indicator variables. Additionally, the loading factor values of each indicator are above 0.5, suggesting that the indicators of average per capita expenditure, mean year school and percentage of households are valid for measuring socioeconomic status. As a proxy for average family income, average per capita expenditure has the most significant explained variance compared to other indicators. The same pattern is observed in other latent variables, where each outer loading on its indicators exceeds 0.5. The AVE value for each latent variable is more significant than 0.5. It indicates that these variables can substantially explain the variance of their indicators by more than 50%. Furthermore, discriminant validity checks are necessary to ensure that each latent variable formed is unique and does not capture similar phenomena.

Table 3. Discriminant validity-HTMT matrix

	Socioeconomic	Health Access	Food Intake	Undernutrition
Socioeconomic				
Health Access	0.731			
Food Intake	0.798	0.633		
Undernutrition	0.486	0.775	0.811	

From the HTMT matrix presented in Table 3, it can be observed that none of the HTMT values between latent variables exceed 0.85. It indicates that each formed latent variable is distinct from the others. It can be inferred that the requirements for discriminant validity have been met.

3.2 Structural Model Evaluation

Structural models, or inner models, delineate the associations among latent variables. In Partial Least Squares (PLS), the path parameter coefficient is derived from the weight of the inner model, which is determined by the t-statistic value obtained during the bootstrapping stage.

Table 4. Path Parameter Coefficients

Variable	Path Coefficient	Standard error	T-statistic	p-value
Food Intake → Undernutrition	-0.535	0.159	3.361	0.001
Health Access → Food Intake	0.324	0.177	1.831	0.067
Health Access → Undernutrition	-0.351	0.142	2.476	0.013
Socioeconomic → Food Intake	0.457	0.196	2.330	0.020

Based on the results presented in Table 4, two structural equations are obtained, namely:

$$\text{Undernutrition} = -0.535\ \text{Food Intake} - 0.351\ \text{Health Access} \qquad (8)$$

$$\text{Food Intake} = 0.324\ \text{Health Access} + 0.457\ \text{Socioeconomic} \qquad (9)$$

In Table 4 and Equation (8), it is known that food intake has a significant negative effect on undernutrition, indicating that improving food intake quality reduces undernutrition in toddlers. A 10% increase in food intake will directly decrease undernutrition by 5.35%. These findings are consistent with a study conducted in Banda Aceh, which revealed that toddlers with insufficient food intake have a fivefold higher risk of experiencing malnutrition [42]. Undernutrition is also significantly affected directly by health access, whereby regions with improved health access demonstrate lower rates of undernutrition. These findings align with research on the double burden of malnutrition, indicating that health access, including easy access to essential healthcare facilities for pregnant women, complete child immunization, and access to clean water and adequate sanitation, adversely affects such health concerns [43]. Other research indicates that children living in households with food insecurity were 2.15 times more likely to experience underweight and three times more likely to experience stunting compared to children in food-secure households [44].

Equation (9) illustrates that food intake is a function of health access and socioeconomic factors. This finding is consistent with previous research [43], indicating that health access has a positive but insignificant effect on food intake. In contrast, socioeconomic variables have a significant positive impact on food intake. It relates to the notion that increased food expenditure enhances dietary diversity [45]. From Equations (8) and (9), it is also evident that the latent variables of health access and socioeconomic status indirectly correlate with undernutrition through food intake. Therefore, the magnitude of the indirect effect of these latent variables on undernutrition can be determined.

Table 5. Specific indirect Effect

Variable	Indirect Effect	Standard error	T-statistic	p-value
Health Access → Food Intake → Undernutrition	-0.173	0.128	1.351	0.177
Socioeconomic → Food Intake→ Undernutrition	-0.244	0.115	2.134	0.033

Based on Table 5, the socioeconomic variable significantly negatively affects undernutrition through food intake. A 10% increase in socioeconomic will indirectly decrease undernutrition by 2.24%. It implies that better socioeconomic conditions, which depict prosperity and development, will indirectly reduce undernutrition. This finding aligns with the conceptual framework adopted from the conceptual framework regarding factors associated with wasting and underweight in toddlers in Northern Africa, indicating that socioeconomic factors affect wasting and underweight through dietary intake [14]. Meanwhile, health access does not have a significant indirect effect or only has a direct effect on undernutrition in toddlers. This result also reinforces previous research indicating that health access directly impacts undernutrition [6].

Table 6. **Total Effect**

Variable	Path Coefficient	p-value
Food Intake → Undernutrition	-0.535	0.001
Health Access → Food Intake	0.324	0.067
Health Access → Undernutrition	-0.524	0.000
Socioeconomic → Food Intake	0.457	0.020
Socioeconomic → Undernutrition	-0.224	0.033

Table 6 displays the magnitude of the total effect of each exogenous variable on the endogenous variable. This total effect combines both direct and indirect effects. Based on Table 6, it can be concluded that the variables with the most potent effect on undernutrition are food intake and health access.

Total effect = direct effect + indirect effect

Total effect of socioeconomic = 0 + 0.457 x -0.535 = -0.244

Total effect of health access = -0.351 + (0.324 x -0.535) = -0.524

A 10% increase in socioeconomic will decrease undernutrition by 2.24%, while a 10% increase in health access will decrease undernutrition by 5.24%.

Table 7. **R-Squared Value**

Endogenous Variable	R^2
Undernutrition	0.608
Food Intake	0.447

The R^2 values presented in **Table 7** indicate the amount of variance in the latent variables of undernutrition and food intake explained by their exogenous variables. The R^2 value for undernutrition is 0.608, meaning that 60.8% of the variance in undernutrition in toddlers can be explained by the variables of food intake, health access, and socioeconomic status. This figure falls within the moderate category. Meanwhile, the R^2 value for food intake is 0.447, suggesting that 44.7% of the variance in food intake can be explained by socioeconomic and health access variables.

4. CONCLUSIONS

This study employs PLS-SEM to model undernutrition in toddlers in the regencies/cities of Aceh Province. The modeling results indicate that undernutrition is directly affected by health access and food intake. At the same time, socioeconomic factors exert an indirect effect, all of which significantly have negative effects. Additionally, it was found that food intake is the primary factor influencing undernutrition in Aceh toddlers.

A recommendation for policymakers to address the undernutrition issue in toddlers would be to prioritize enhancing food intake quality, given its identified significance as the primary determinant of undernutrition. Improving the quality of food intake can be achieved by strengthening adequate food consumption by increasing the diversity of food intake and the level of sufficient animal food consumption, as well as vegetables and fruits. Furthermore, for future research endeavors, including additional variables and food indicators is recommended to establish a more robust and comprehensive model.

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