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MODELING CHILD MALNUTRITION IN EAST JAVA USING THE INTEGRATION OF PARTIAL LEAST SQUARE WITH IMPORTANCE-PERFORMANCE ANALYSIS

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Abstract: Child malnutrition remains a persistent public health concern in Indonesia, particularly in East Java, where stunting and undernutrition rates remain high despite national progress. Malnutrition in children is a multidimensional issue, influenced not only by dietary intake and disease but also by socio-economic conditions, caregiving practices, and environmental health factors such as access to clean water, sanitation, and health services. Addressing this complexity requires robust analytical methods. This study applies Partial Least Squares–Importance Performance Analysis (PLS-IPA) to model the pathways influencing child malnutrition and identify priority interventions. Results indicate that socio-economic factors act as primary predictors influencing food security, healthcare access, and parenting practices. Among direct determinants, environmental health services, including sanitation, clean water access, and maternal healthcare, show the strongest direct effect in reducing malnutrition. IPA results highlight food security as the most critical intervention priority due to its high importance but moderate field performance. Strengthening socio-economic development, improving food security, and sustaining environmental health interventions are recommended to support long-term reductions in child malnutrition in East Java.

1. INTRODUCTION

Nutritional development in Indonesia is guided by Law No. 36 of 2009 on Health, particularly Article 141, which emphasizes the importance of improving the quality of nutrition through the promotion of diverse, balanced, and safe dietary consumption. Improving nutritional status is critical for developing a healthy, intelligent, and productive population, especially among children under five years old, who are in a crucial phase of physical and cognitive development (Kemenkes, 2020). At this stage, malnutrition not only increases the risk of morbidity and mortality but also impairs cognitive, motor, and psychosocial development. Common forms of child malnutrition include stunting, wasting, and underweight, which serve as key indicators for assessing child health status (Ningsih, 2022). Globally, UNICEF (2021) reported that more than 149 million children under five were stunted and 45 million were wasted, with the majority of cases occurring in Asia (UNICEF, 2021). In Indonesia, the 2018 Basic Health Research (Riskesdas) survey recorded a decline in malnutrition prevalence: underweight decreased from 19.6% to 17.7%, stunting from 37.2% to 30.8%, and wasting from 12.1% to 10.2% (Aryastami and Mubasyiroh, 2023). Although these figures have shown improvement, they remain high according to WHO public health thresholds. East Java is one of the government's priority provinces for stunting reduction, owing to its large population and persistently high prevalence in several districts. According to the 2022 Indonesian Nutrition Status Survey (SSGI), the prevalence of stunting in East Java was 19.2%, with some districts, such as Jember, reporting rates exceeding 30%. These challenges are often linked to limited availability of environmental and health equipment and a lack of cross-sectoral awareness in understanding nutritional issues (Kemenko, 2023).

Child malnutrition is a multifaceted issue shaped by the intricate interaction of food consumption, disease burden, and wider environmental, social, and economic conditions. According to UNICEF's conceptual framework (2021), the causes of malnutrition are categorized into three levels: immediate (e.g., inadequate dietary intake and diseases), underlying (e.g., household food security, caregiving practices, health services, and sanitation), and basic causes, which include socioeconomic conditions, cultural beliefs, education, social capital, and institutional policies (UNICEF, 2021). Given the complexity of the issue, an analytical method capable of thoroughly explaining the relationships among variables is essential. Structural Equation Modeling (SEM) is a multivariate method that combines elements of regression, factor, and path analysis. However, this method requires several assumptions to be met, including multivariate normality, independence of observations, and a large sample size (Hair Jr *et al.*, 2021). In reality, data frequently fail to meet these assumptions, especially when sample sizes are limited or distributions deviate from normality. This limitation calls for an alternative SEM approach that is distribution-free and more flexible. Partial Least Squares Structural Equation Modeling (PLS-SEM) provides an alternative approach since it can handle non-normal data, works effectively with small samples, and is particularly suitable for exploratory studies and theory building (Hair and Alamer, 2022).

Nevertheless, standard PLS-SEM is limited in its ability to support policy-oriented decision-making, as it primarily identifies statistically significant relationships without indicating which determinants should be prioritized for intervention. In the context of child malnutrition, policymakers require not only knowledge of which factors influence nutritional status but also guidance on which factors offer the greatest potential impact if improved. This limitation underscores the need for an analytical extension that goes beyond structural relationships. Over time, researchers have developed several extensions to PLS-SEM to enhance its algorithms and statistical capabilities (Sarstedt *et al.*, 2022). A review of previous studies regarding the application of PLS-SEM indicates that most researchers tend to rely solely on standard PLS path modeling. Among these underutilized techniques, PLS-IPA represents a valuable extension of the basic PLS-SEM approach, providing additional insights that are not obtainable through standard path modeling. The PLS-IPA method enhances analysis by integrating two key dimensions: importance and performance. By assessing both simultaneously, researchers can identify and prioritize which constructs should be targeted for improvement to optimize a specific target construct (Lee, Seow and Xue, 2021). By mapping constructs into importance–performance quadrants, PLS-IPA enables the identification of determinants that exert a strong influence on child malnutrition but demonstrate relatively low performance, thereby representing critical priorities for policy intervention. PLS-IPA serves not only as a robust statistical extension of PLS-SEM, but also as strategic analytical tool that bridges empirical modeling and practical policy formulation.

The application of PLS-IPA is particularly suitable for the case of child malnutrition in East Java, where multiple environmental and health determinants interact and policy resources are limited. The method allows for evidence-based prioritization of interventions by identifying which environmental health factors require urgent improvement to achieve meaningful reductions in malnutrition. This study aims to model the environmental and health determinants of child malnutrition in East Java using the PLS-IPA method. This approach aims to deliver a holistic understanding of the environmental health determinants of child malnutrition while also generating evidence-based policy recommendations to support targeted and effective interventions at the local level.

2. LITERATURE REVIEW

PLS-SEM is a versatile method for examining latent variables represented by multiple indicators. Unlike traditional covariance-based SEM, it adopts a variance-based approach, making it particularly useful when data face challenges such as small sample sizes, non-interval measurements, missing values, non-normal distributions, or multicollinearity. One of its key strengths is its applicability across all measurement scales (nominal, ordinal, interval, and ratio) while relying on more flexible assumptions (Sarstedt, Ringle and Hair, 2021). In PLS-SEM, the core objective is to predict and explain variance in the endogenous latent variables by estimating a network of hypothesized relationships. PLS-SEM prioritizes maximizing the explained variance (R^2) of the dependent constructs, making it particularly suitable for theory development and exploratory modeling (Risher and Hair Jr, 2017).

The structural model specifies theoretical relationships among latent constructs, expressed as Equation (1).

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

where $\boldsymbol{\eta}$ is a random vector of endogenous latent variables with dimension $m \times 1$, $\boldsymbol{\xi}$ is a random vector of exogenous latent variables with dimension $n \times 1$, $\mathbf{B}$ is the coefficient matrix of the endogenous latent variables with dimension $m \times m$, and $\boldsymbol{\Gamma}$ is the coefficient matrix of the exogenous latent variables representing the relationships between $\boldsymbol{\xi}$ and $\boldsymbol{\eta}$ with dimension $m \times n$. The vector $\boldsymbol{\zeta}$ denotes the random error term with dimension $m \times 1$. In this notation, m represents the number of endogenous latent variables, while n represents the number of exogenous latent variables. The measurement model defines how latent constructs relate to their observed indicators, either reflectively or formatively. In reflective models, indicators mirror their latent variable, as represented by Equations (2) and (3).

$$y_{(p\times1)} = \boldsymbol{\Lambda}_{y(p\times m)} \times \boldsymbol{\eta}_{(m\times1)} + \boldsymbol{\varepsilon}_{(p\times1)} \tag{2}$$

$$x_{(q\times1)} = \boldsymbol{\Lambda}_{x(p\times n)} \times \boldsymbol{\xi}_{(n\times1)} + \boldsymbol{\delta}_{(q\times1)} \tag{3}$$

where $\boldsymbol{\Lambda}_y$ and $\boldsymbol{\Lambda}_x$ are loading matrices. Because latent variables are unobservable, PLS estimates them as linear composites of observed indicators using optimally derived weights (Hair *et al.*, 2010). The PLS algorithm is carried out in the following stages (Memon *et al.*, 2021):

1. Initialize the measurement model weights.
$$\tilde{w}_{jh} = 1 \tag{4}$$
2. Measurement model estimation.
$$Y_j = \sum_{h=1}^{H} w_{jh} x_{jh} \tag{5}$$
3. Determine the weight of the structural model.
$$v_{ji} = \begin{cases} cor(Y_i, Y_j) & Y_i \text{ as a predictor of } Y_j \\ reg(Y_i, Y_j) & Y_j \text{ as a predictor of } Y_i \end{cases} \tag{6}$$
4. Structural model parameter estimation.
$$\tilde{Y}_j = \sum_{i=1, i\neq j}^{I} v_{ji} Y_i \tag{7}$$
5. Updating the measurement model weights.
$$\hat{\mathbf{w}}_j = \left(\tilde{\mathbf{Y}}_j^{\mathbf{T}} \tilde{\mathbf{Y}}_j\right)^{-1} \left(\tilde{\mathbf{Y}}_j^{\mathbf{T}} \mathbf{x}_j\right) \tag{8}$$

6. Path estimation.

$$\hat{\boldsymbol{\beta}}_{\mathrm{i}} = \left(\mathbf{Y}_{\mathrm{j}}^{\mathrm{T}}\mathbf{Y}_{\mathrm{j}}\right)^{-1}\left(\mathbf{Y}_{\mathrm{j}}^{\mathrm{T}}\mathbf{Y}_{\mathrm{i}}\right) \tag{9}$$

7. Loading coefficient estimation.

$$x_{jh} = \hat{\lambda}_{jh} Y_j \tag{10}$$

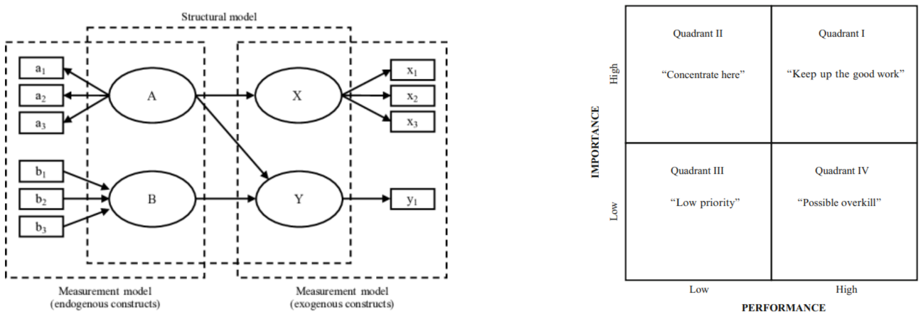
$$\hat{\lambda}_{jh} = \hat{\mathbf{w}}_{\mathrm{j}} = \left(\mathbf{Y}_{\mathrm{j}}^{\mathrm{T}}\mathbf{Y}_{\mathrm{j}}\right)^{-1}\mathbf{Y}_{\mathrm{j}}^{\mathrm{T}}\mathbf{x}_{\mathrm{j}} \tag{11}$$

PLS is a composite-based structural equation modeling approach where latent constructs are represented as weighted combinations of their indicator (Lohmöller, 2013). This method allows researchers to calculate composite scores, which are frequently interpreted as performance values. These scores reflect respondents' evaluations of specific attributes. For example, when respondents express maximum satisfaction with a construct, it is reflected as a 100% performance score (Sarstedt *et al.*, 2024). This foundational characteristic of PLS-SEM has been applied in developing standardized performance indices, such as the Swedish Customer Satisfaction Barometer and the American Customer Satisfaction Index (Fornell *et al.*, 1996). In PLS-IPA, the average importance scores are plotted along the horizontal axis, while performance scores appear on the vertical axis (Hauff *et al.*, 2024).

To evaluate importance, PLS-IPA typically uses total effects from the structural model, which account for both direct and indirect relationships between constructs. This approach provides a comprehensive view of how each antecedent construct influences the target outcome, either directly or through mediating variables. Performance is represented by the average score of each construct. These scores can be based on standardized or unstandardized data. Standardized scores are calculated using z-transformations, but because they result in a mean of zero and a standard deviation of one, they are not useful for performance interpretation. Instead, unstandardized construct scores are preferred, as they directly reflect the original measurement scales, making them easier to interpret in practical contexts. When using unstandardized scores, differences in measurement scales among indicators can complicate interpretation. To address this, the indicator data are typically rescaled to a 0–100 range, where 0 represents the lowest possible performance and 100 represents the highest, as shown in Equation (12). Transformation standardizes performance metrics across constructs and ensures comparability (Hauff *et al.*, 2024).

$$x_{ij}^{rescaled} = \frac{E[x_{ij}] - \min[x_i]}{\max[x_i] - \min[x_i]} . 100 \tag{12}$$

The rescaled latent variable scores are computed as linear combinations of the rescaled indicators and adjusted outer weights. These outer weights are derived by converting standardized weights into unstandardized form and normalizing them so that their sum equals one within each measurement model. The final rescaled scores, ranging from 0 to 100, represent the performance of each construct. In the resulting PLS-IPA, constructs are positioned within four quadrants based on their importance and performance levels. Constructs that are both highly important and high-performing should be maintained, while those that are important but underperforming should be prioritized for improvement. Constructs with low importance and performance may require less attention, while those with high performance but low importance might indicate areas of over-investment. This strategic mapping guides decision-makers in identifying key areas for intervention to optimize outcomes effectively (Hauff *et al.*, 2024). Figure 1(a) represents the PLS-SEM model, while Figure 1(b) presents the PLS-IPA output.



(a) (b)

Figure 2. PLS-SEM Model (a) and PLS-IPA Map (b)

3. RESEARCH METHOD

This study utilized secondary data sourced from the 2022 East Java Health Profile, the 2022 East Java Education Statistics, the 2022 Food Security Index Book, and various publications from Statistics Indonesia (BPS) published in 2022. The research focused on five latent variables. Each latent variable was measured using several indicators, which were developed based on a conceptual framework (UNICEF, 2021). Details of the latent and manifest variables applied in this study are presented in Table 1.

Table 1. Research Variables

Latent Variable	Manifest Variable	
	$X_{1.1}$	Per capita expenditure
Socio-Economic	$X_{1.2}$	Average years if schooling (year)
	$X_{1.3}$	Percentage of poor population (percent)
	$Y_{1.1}$	Proportion of infants exclusively breastfed (percent)
	$Y_{1.2}$	Proportion of infants receiving early initiation of breastfeeding (percent)
Parenting	$Y_{1.3}$	Proportion of toddlers receiving vitamin A (percent)
	$Y_{1.4}$	Proportion of toddlers fully immunized (percent)
	$Y_{1.5}$	Proportion of neonatal visits for infants (percent)
Food Security	$Y_{2.1}$	Food security index score (percent)
	$Y_{3.1}$	Coverage of infant health services (percent)
	$Y_{3.2}$	Proportion of pregnant women receiving iron tablets (percent)
Health and Environmental Services	$Y_{3.3}$	Proportion of postpartum contraceptive users (percent)
	$Y_{3.4}$	Proportion of pregnant women with obstetric complications treated (percent)
	$Y_{3.5}$	Percentage of households with access to safe drinking water (percent)
	$Y_{3.6}$	Percentage of households with access to proper sanitation (percent)
	$Y_{3.7}$	Coverage of antenatal care for pregnant women (percent)
	$Y_{4.1}$	Prevalence of stunting (percent)
Malnutrition Status	$Y_{4.2}$	Prevalence of wasting (percent)
	$Y_{4.3}$	Prevalence of underweight (percent)

The relationships between the latent variables and their indicators, as well as the relationships between exogenous and endogenous latent variables, are illustrated using path diagram. The model employed is a reflective measurement model, as shown in Figure 2. The analysis was conducted using Partial Least Squares integrated with Importance-Performance Analysis, following these steps:

1. Theoretical Framework and Model Specification: Develop the measurement and structural models based on theoretical and empirical literature.
2. Data Preparation and Exploration: Collect, preprocess, and explore the data to assess distributional characteristics and data quality.
3. PLS-SEM Model Estimation: Estimate latent variable scores, outer loadings, and path coefficients using a variance-based PLS approach.

4. Measurement and Structural Model Evaluation: Assess construct validity, reliability, and structural relationships using AVE, CR, R^2, and bootstrap significance testing.
5. Model Refinement and Selection: Refine and select the best-fitting model based on evaluation results.
6. Importance-Performance Analysis: Compute importance values using total effects and performance values using rescaled latent variable and indicator scores.
7. Importance-Performance Mapping and Interpretation: Construct IPA quadrant maps and interpret the results to identify priority areas for intervention.

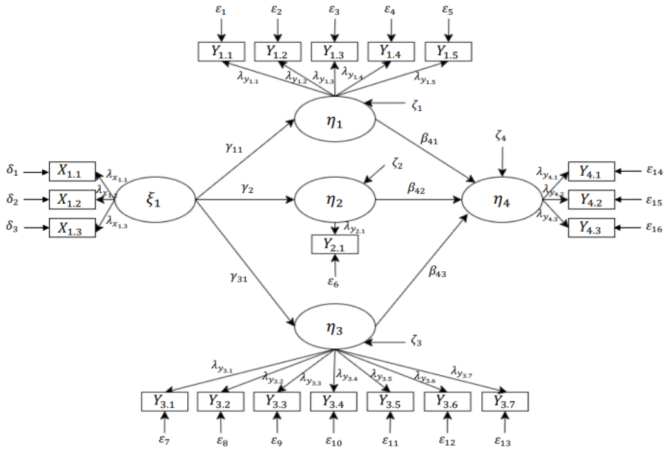


Figure 2. Research Path Diagram

4. RESULT AND DISCUSSION

The modeling using the PLS-SEM approach was conducted to identify valid and reliable indicators for the latent variables within the child malnutrition model in East Java Province. To identify indicators that are both valid and reliable for each latent variable in the model, an evaluation of the measurement model is conducted as an initial step.

Table 2. Loading Factor for Each Valid Indicator

Latent Variable	Manifest Variable	Loadings
Socio-Economic	$X_{1.1}$	0.961
	$X_{1.2}$	0.970
Parenting	$Y_{1.1}$	0.920
	$Y_{1.3}$	0.715
	$Y_{1.4}$	0.604
Food Security	$Y_{2.1}$	1.000
Health and Environmental Services	$Y_{3.2}$	0.543
	$Y_{3.6}$	0.824
	$Y_{3.7}$	0.791
Malnutrition Status	$Y_{4.1}$	0.947
	$Y_{4.2}$	0.791
	$Y_{4.3}$	0.970

Based on the results presented in Table 2, indicator $X_{1.2}$ was found to have the highest loading factor among the socio-economic indicators. This suggests that the indicator "Average Years of Schooling" has the strongest contribution in representing the socio-economic construct. Similarly, for the parenting latent variable, the indicator "Proportion of Infants Exclusively Breastfed" demonstrated the highest loading factor, indicating that this variable most significantly explains the parenting construct. Within the Health and Environmental Services latent variable, the indicator "Percentage of Households with Access to Proper Sanitation" showed the greatest influence in representing the construct, as indicated by its highest loading factor. Regarding the Malnutrition Status latent variable, the "Prevalence of Underweight" indicator exhibited the strongest contribution to the construct.

Table 3. Reliability Evaluation with Composite Reliability

Latent Variable	Composite Reliability
Socio-Economic	0.965
Parenting	0.797
Food Security	1.000
Health and Environmental Services	0.739
Malnutrition Status	0.932

Following the evaluation of discriminant validity, a reliability assessment was conducted to determine whether each construct demonstrates sufficient internal consistency in measuring its corresponding latent variable. This assessment was performed using composite reliability as the measurement indicator. As presented in Table 3, the composite reliability values for all latent variables exceed the recommended threshold of 0.70. This result indicates that each latent construct demonstrates strong internal consistency and can be considered a reliable measurement tool in the model.

Table 4. Model Determination Coefficient Value

Latent Variable	R^2	Criteria
Parenting	0.797	Weak
Food Security	1.000	Moderate
Health and Environmental Services	0.739	Moderate
Malnutrition Status	0.932	Weak

Following the evaluation of the measurement model, the structural model was subsequently assessed to examine the relationships among the latent variables. This evaluation focused on several key indicators: the coefficient of determination (R^2), the Q-square predictive relevance, and the goodness of fit (GoF) index (Tenenhaus *et al.*, 2005). Based on Table 4, The R^2 value for the latent variable food security is 0.524, indicating that 52.4% of the variance in food security can be explained by the socio-economic latent variable, while the remaining 47.6% is attributed to other factors not included in the model. For the parenting latent variable, the R^2 value is 0.181, meaning that 18.1% of its variance is explained by the socio-economic variable, with the remaining 81.9% explained by variables outside the model. Similarly, 48.7% of the variance in health and environmental services is explained by the socio-economic construct, as reflected by an R^2 value of 0.487, while the remaining 51.3% is influenced by external factors. Finally, the variance in child malnutrition, as represented by the malnutrition status variable, is explained by food security, parenting, and health and environmental services by only 9%, indicating that 91% of its variance is explained by other unobserved factors outside the structural model.

The Q^2 predictive relevance value is obtained based on the calculation results, as represented by Equation 13.

$$\begin{aligned} Q^2 &= 1-\left(\left(1-R_1^2\right)\left(1-R_2^2\right)\left(1-R_3^2\right)\left(1-R_4^2\right)\right) \\ &= 1-\left(\left(1-0{,}181\right)\left(1-0{,}524\right)\left(1-0{,}487\right)\left(1-0{,}090\right)\right) \\ &= 0{,}818 \end{aligned} \tag{13}$$

Q^2 predictive relevance value was calculated to assess the predictive accuracy of the structural model. The obtained Q^2 value indicates that the model possesses adequate predictive relevance, confirming that the structural equations have reasonable predictive capability.

In addition, the overall model fit was evaluated using the Goodness of Fit (GoF) index. The GoF value ranges from 0 to 1, with thresholds of 0.10 (weak), 0.25 (moderate), and 0.36 (strong). The GoF value for the model was calculated as follows, providing a comprehensive measure of how well the measurement and structural components fit together within the model.

$$
\begin{aligned}
GoF &= \sqrt{\overline{AVE} \times \overline{R^2}} \\
&= \sqrt{0.692 \times 0.3205} \\
&= 0.471
\end{aligned}
\tag{14}
$$

Based on Equation 14, the Goodness of Fit (GoF) value obtained is 0.471. This value exceeds the recommended threshold of 0.36, which indicates a strong model fit. Therefore, it can be concluded that the structural model demonstrates a good overall fit and possesses a strong explanatory power in representing the data.

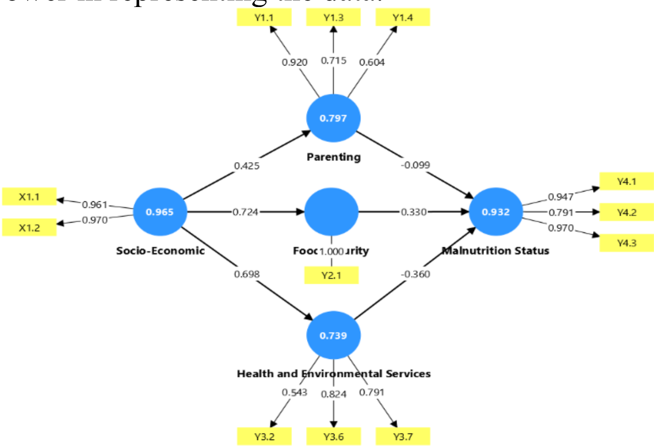


Figure 3. Diagram and Coefficient Values of PLS Model

Based on the structural model parameter coefficients presented in Figure 3, the structural model for this study can be formulated in Equations (15) – (18).

$$\eta_1 = 0.425\xi_1 + \zeta_1 \tag{15}$$

$$\eta_2 = 0.724\xi_1 + \zeta_2 \tag{16}$$

$$\eta_3 = 0.698\xi_1 + \zeta_3 \tag{17}$$

$$\eta_4 = -0.099\eta_1 + 0.33\eta_2 - 0.36\eta_3 + \zeta_4 \tag{18}$$

Following the evaluation and estimation of both the measurement model and the structural model, hypothesis testing was conducted based on the parameter estimation results from both models. The parameters evaluated include λ, γ, and β, with significance testing performed using a resampling bootstrap method involving B = 5000 replications. The t-statistic was used as the test statistic within the PLS-SEM framework.

Table 5. Measurement Model Testing Results with Resampling Bootstrap

Latent Variable	Manifest Variable	Loadings	T-Statistics	P-value	Information
Socio-Economic	$X_{1.1}$	0.961	85.815	0.000	Valid, significant
	$X_{1.2}$	0.970	140.565	0.000	Valid, significant
Parenting	$Y_{1.1}$	0.920	5.034	0.000	Valid, significant
	$Y_{1.3}$	0.715	2.189	0.029	Valid, significant
	$Y_{1.4}$	0.604	1.988	0.046	Valid, significant
Food Security	$Y_{2.1}$	1.000	*	*	
Health and Environmental Services	$Y_{3.2}$	0.543	1.975	0.048	Valid, significant
	$Y_{3.6}$	0.824	11.635	0.000	Valid, significant
	$Y_{3.7}$	0.791	6.212	0.000	Valid, significant
Malnutrition Status	$Y_{4.1}$	0.947	6.038	0.000	Valid, significant
	$Y_{4.2}$	0.791	4.37	0.000	Valid, significant
	$Y_{4.3}$	0.970	6.815	0.000	Valid, significant

Based on the results presented in Table 5, the t-statistics values for all indicators relative to their respective latent variables exceed the critical threshold of 1.96. This indicates that each indicator is statistically significant at the 5% significance level (two-tailed test). In other words, all the indicators used in the measurement model contribute significantly to explaining their corresponding latent constructs. These findings confirm that each indicator is valid in measuring its respective latent variable, as each loading factor is statistically different from zero. This supports the conclusion that the measurement model has been appropriately specified, with each observed indicator providing meaningful and reliable information about the underlying construct it represents. The significance of all loading factors suggests that the model effectively captures the constructs intended in the conceptual framework. In PLS-SEM, no distributional assumption tests are required because this method is assumption-free (distribution-free).

Table 6. Structural Model Testing Results with Resampling Bootstrap

Path	Coefficient	T-Statistics	P-value
Socio-Economic → Parenting	0.425	2.710	0.007
Socio-Economic → Food Security	0.724	10.396	0.000
Socio-Economic → Health and Environmental Services	0.698	11.411	0.000
Parenting → Malnutrition Status	-0.099	0.378	0.705
Food Security → Malnutrition Status	0.330	1.142	0.254
Health and Environmental Services → Malnutrition Status	-0.360	1.971	0.049

Based on the results presented in Table 6, socio-economic factors were found to have a significant positive effect on parenting, with a path coefficient of 0.425, a t-statistic of 2.710, and a p-value of 0.007. Since the t-statistic exceeds the critical value of 1.96 and the p-value is lower than the significance level of 0.05, it can be concluded that socio-economic improvements are associated with enhanced parenting practices. Similarly, socio-economic factors significantly influence food security, indicated by a high coefficient of 0.724, a t-statistic of 10.396, and a p-value of 0.000. This result confirms that higher socio-economic status contributes positively to food security conditions. A similar pattern is observed in the relationship between socio-economic factors and health and environmental services, where a significant positive effect is recorded, with a coefficient of 0.698, a t-statistic of 11.411, and a p-value of 0.000. These findings demonstrate that better socio-economic conditions support improvements in health services and environmental quality.

In contrast, the effect of parenting on child malnutrition status was found to be insignificant, with a negative path coefficient of -0.099, a t-statistic of 0.378, and a p-value of 0.705. This indicates that variations in parenting, as defined in this model, do not have a statistically significant direct influence on the malnutrition status of children under five. Similarly, food security does not show a significant direct effect on malnutrition status, as indicated by a coefficient of 0.330, a t-statistic of 1.142, and a p-value of 0.254. Although the relationship is positive, the effect is not strong enough to be considered statistically significant at the 5% level.

Interestingly, health and environmental services exhibit a significant negative influence on malnutrition status, with a coefficient of -0.360, a t-statistic of 1.971, and a p-value of 0.049. This indicates that improvements in health and environmental services are associated with reductions in child malnutrition. The negative relationship suggests that as access to and quality of health and environmental services improve, the prevalence of malnutrition among children under five is likely to decline. Overall, the structural model results highlight the critical role of socio-economic conditions in shaping key determinants such as parenting, food security, and health services. However, among the direct factors influencing child malnutrition, only health and environmental services show a statistically significant effect in this study.

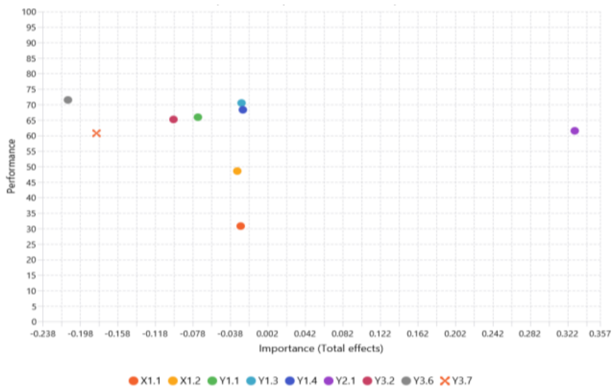


Figure 4. PLS-IPA Map

Based on the results of the Importance-Performance Map Analysis, as presented in Figure 4, it is evident that the indicator Y2.1 (Food Security Index Score) emerges as the most critical priority in efforts to improve child malnutrition outcomes in East Java. This indicator demonstrates the highest importance value (total effects) while also achieving relatively high performance. The significant total effect suggests that improvements in food security directly contribute to reducing child malnutrition rates. This finding aligns with fundamental theories in nutritional science and social welfare, which emphasize that access to sufficient, safe, and nutritious food is essential for children's optimal growth and health.

In contrast, other indicators such as X1.1 (Per Capita Expenditure) and X1.2 (Average Years of Schooling) show lower levels of importance in this model, though their performance levels vary. The relatively lower importance of these socio-economic indicators in explaining malnutrition status could reflect the mediating role of other factors like food security and health services. While economic capacity and education level are theoretically fundamental in enabling better access to food and health care, their direct statistical impact on malnutrition outcomes appears weaker in this specific context. This suggests that improvements in socio-economic status may influence malnutrition more indirectly, through other mediating latent variables.

Furthermore, the Health and Environmental Services indicators, particularly Y3.2 (Proportion of Pregnant Women Receiving Iron Tablets) and Y3.6 (Access to Proper Sanitation), present moderate to high performance but relatively lower importance in reducing malnutrition directly. Nevertheless, as reflected in the structural model results, health services collectively show a statistically significant negative relationship with malnutrition status. This relationship is consistent with health behavior theories, which highlight that improving maternal and child healthcare, along with access to sanitation, contributes to better nutritional outcomes by reducing disease burden and enhancing nutrient absorption. The Parenting indicators, such as Y1.1 (Exclusive Breastfeeding Proportion) and Y1.4 (Immunization Coverage), occupy a moderate position in both importance and performance dimensions. These findings suggest that while parenting practices are essential for child health, their direct contribution to reducing malnutrition rates is less significant statistically. This may be due to overlapping influences with health service access or the presence of stronger structural factors like food availability. From a social perspective, cultural beliefs and local childcare practices could also modulate the effectiveness of parenting interventions, further explaining these results.

5. CONCLUSION

This research presents an in-depth investigation into the environmental and health factors affecting child malnutrition in East Java, utilizing PLS-IPA approach. The findings indicate that socio-economic elements are crucial primary determinants that impact food security, parenting quality, and health-related services. The results from the structural model indicated that socio-economic status has a substantial effect on food security, showing the highest path coefficient of 0.724, followed by its effect on health services (0.698) and parenting practices (0.425). This suggests that enhancing economic conditions, such as household income and educational attainment, is essential for bolstering these interrelated factors that influence child nutrition. Additional analysis showed that among the three primary determinants, health and environmental services exerted a direct and statistically significant effect on lowering malnutrition rates, as evidenced by a negative path coefficient of -0.360 and a p-value that is below the 5% significance threshold. This highlights the critical importance of access to healthcare, coverage for maternal care, and essential infrastructure like clean water and sanitation in combating malnutrition issues. In contrast, while food security and parenting factors had positive coefficients, they did not have a significant direct effect on malnutrition status. This might indicate that their impacts could be indirect or mediated. The Importance-Performance Map Analysis provided essential insights for guiding intervention priorities. The Food Security Index stood out as the most significant factor with moderately effective performance, identifying it as a crucial area needing strategic focus. Health-related indicators, such as antenatal care access and the availability of safe drinking water, showed high performance but moderate importance, implying these aspects are effectively managed yet should be preserved to ensure sustained outcomes.

From these insights, several recommendations can be articulated. First, government agencies and policymakers ought to focus on improving food security within the region, as this factor showed the strongest overall influence on child nutrition. Strategies should aim not just at enhancing food availability but also at ensuring economic access. Second, the health sector should continue to bolster healthcare services and environmental resources. Initiatives related to maternal health, sanitation, and clean water supply need to remain priorities because of their significant influence on reducing malnutrition. Third, while parenting practices did not show a direct impact in this research, community educational initiatives aimed at mothers and caregivers should still be prioritized. Such programs can indirectly promote better child nutrition through improved feeding practices, hygiene habits, and early childhood care. Lastly, future studies should investigate how healthcare access and food security may mediate the effects of socio-economic factors on child malnutrition. Expanding the research to encompass larger and more varied samples or integrating longitudinal data would enhance the understanding of these causal relationships.

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