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Comparing Weighting Schemes in Modeling Child Malnutrition in East Java

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Abstract

Partial Least Squares is increasingly used as an alternative to covariance-based SEM due to its flexibility in handling non-normal data, small sample sizes, and complex models, as well as its ability to operate under different inner weighting schemes. However, empirical studies rarely compare these weighting schemes, even though they may influence measurement validity and structural interpretations. This study applies PLS-SEM using both the path and factor weighting schemes to evaluate their performance in modeling child malnutrition. Child malnutrition remains a major public health concern, as it is driven by the interaction of socioeconomic, food security, parenting, and access to basic services. The study estimates and evaluates measurement and structural models using PLS under path and factor schemes. The findings show that both schemes produce acceptable measurement and structural models, but the path scheme yields more consistent indicator significance and more stable structural relationships, while the factor scheme is more sensitive to weaker indicators, leading to some nonsignificant loadings and paths. The results suggest that although both weighting schemes are suitable for exploratory analysis, the path weighting scheme provides more robust and interpretable results for explaining child malnutrition, highlighting the importance of weighting scheme selection in applied PLS-SEM research.

Keywords: *Child malnutrition, Factor weighting scheme, Partial Least Square, Path weighting scheme, Structural Equation Modeling*

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1. INTRODUCTION

Structural Equation Modeling (SEM) is a multivariate statistical technique that integrates regression, factor, and path analysis to examine complex relationships among observed and latent variables. Despite its extensive use, conventional covariance-based SEM is constrained by strict assumptions, including multivariate normality, independence of observations, and the need for large sample sizes. In applied research, these assumptions are often violated, particularly when using secondary data, working with limited samples, or encountering non-normal data distributions [1]. To overcome these limitations, Partial Least Squares SEM (PLS-SEM) has been widely adopted as a variance-based alternative. PLS-SEM offers greater flexibility, does not require distributional assumptions, and performs effectively with smaller samples, making it well suited for exploratory and prediction-oriented studies [2].

A key methodological feature of PLS-SEM is the availability of different inner weighting schemes for parameter estimation. The path weighting scheme emphasizes structural relationships among latent variables by maximizing explained variance, while the factor weighting scheme is based on correlations among latent constructs and yields estimates closer to traditional factor analysis [3]. Although methodological studies have shown that these schemes can lead to differences in indicator loadings, structural coefficients, and model evaluation metrics, most empirical applications rely on a single weighting scheme, typically the path scheme, without systematically examining the robustness of results across alternative estimation approaches [4]. This methodological gap underscores the importance of comparative analysis to strengthen inference and enhance transparency in PLS-SEM applications.

Within this methodological context, child malnutrition remains a major public health concern in Indonesia, particularly among children under five years old who are in a critical phase of physical and cognitive development. Nutritional development in Indonesia is regulated by Law No. 36 of 2009 on Health, which emphasizes improving nutrition quality through the promotion of diverse, balanced, and safe diets [5]. Malnutrition during early childhood increases the risk of morbidity and mortality and impairs cognitive, motor, and social development. The most commonly used indicators to assess child malnutrition are stunting, wasting, and underweight [6].

Globally, UNICEF (2021) reported that approximately 149 million children under five were stunted and 45 million were wasted, with Asia accounting for the majority of cases [7]. In Indonesia, the 2018 Basic Health Research (Riskesdas) recorded declines in malnutrition prevalence, including a reduction in stunting from 37.2% to 30.8%; however, these levels remain above WHO public health thresholds [8]. At the regional level, East Java remains a priority province for stunting reduction, as prevalence rates in several districts continue to exceed national targets [9]. These persistent challenges reflect the complex interplay of socioeconomic conditions, household food security, caregiving practices, and access to basic services [10].

Building on both the substantive and methodological literature, this study contributes to existing research by simultaneously examining the determinants of child malnutrition and systematically comparing the path and factor weighting schemes within the PLS-SEM framework. This dual focus represents an innovative contribution, as it not only provides empirical insights into child malnutrition but also evaluates the sensitivity and robustness of model results to different estimation schemes. By integrating substantive analysis with methodological comparison, the study enhances the reliability of findings and offers stronger evidence to support data-driven policy formulation.

2. METHOD

2.1. Partial Least Squares Structural Equation Modeling Concept

Partial Least Squares Structural Equation Modeling is a flexible analytical approach for examining latent constructs measured by multiple indicators. Unlike covariance-based SEM, PLS-SEM adopts a variance-based estimation procedure, making it particularly appropriate for empirical conditions characterized by small sample sizes, non-normal data distributions, missing values, multicollinearity, or the use of non-interval measurement scales. A key advantage of PLS-SEM is its ability to accommodate all types of measurement scales—nominal, ordinal, interval, and ratio—while relying on fewer and less restrictive assumptions [11]. The primary objective of PLS-SEM is to predict and explain variance in endogenous latent variables through the estimation of a network of hypothesized relationships, with particular emphasis on maximizing the coefficient of determination (R^2) for dependent constructs. This focus makes PLS-SEM especially suitable for exploratory research and theory development [2].

The structural model in PLS-SEM specifies the theoretical relationships among latent variables and is expressed in Equation (1).

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

where $\boldsymbol{\eta}$ and ξ denote endogenous and exogenous latent variables, respectively. The matrices $\mathbf{B}$ and $\mathbf{\Gamma}$ contain path coefficients that represent direct and indirect effects among constructs [12]. The measurement model defines the relationships between latent variables and their observed indicators and can be specified as either reflective or formative. In reflective measurement models, indicators are assumed to be manifestations of the underlying latent construct, as shown in 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 $\boldsymbol{\Lambda}_x$ represent the loading matrices. Since latent variables are not directly observable, PLS-SEM estimates them as linear composites of observed indicators using optimally derived weights [13].

The PLS algorithm is implemented through several iterative steps [14].

i. Initial weights for the measurement model are assigned.

$$\tilde{w}_{jh} = 1 \tag{4}$$

ii. Estimation of the measurement model.

$$Y_j = \sum_{h=1}^{H} w_{jh} x_{jh} \tag{5}$$

iii. Determine the weight of the structural model.

In the PLS-SEM algorithm, a crucial step is the determination of inner weights, which define how latent variables are related within the structural model. The specification of these weights depends on the selected weighting scheme, with the most commonly used being the path scheme and the factor scheme. Each scheme applies different principles in assigning inner weights, which may lead to differences in latent variable scores and, consequently, structural parameter estimates [15].

a. Path Weighting Scheme

In the path scheme, latent variables are classified into antecedents (predictors) and followers (responses) based on the assumed causal relationships in the structural model. When a latent variable Y_i is specified as a response variable influenced by another latent variable Y_j, the inner weight is defined as the correlation between Y_i and Y_j. Conversely, when Y_i acts as a predictor of Y_j, the inner weight is obtained from the regression coefficient of Y_i in a multiple regression model where Y_j is the dependent variable. This approach explicitly incorporates the direction of causality and prioritizes variance explanation in endogenous constructs. The definition of inner weights under the path scheme is formally expressed in Equation (6).

$$v_{ji} = \begin{cases} cor(Y_i, Y_j) & Y_i \ as\ a\ predictor\ of\ Y_j \\ reg(Y_i, Y_j) & Y_j \ as\ a\ predictor\ of\ Y_i \end{cases} \tag{6}$$

b. Factor Weighting Scheme

In contrast, the factor scheme does not distinguish latent variables strictly based on causal direction. Instead, it considers both the strength and sign of the relationships among latent constructs in the structural model. Under this scheme, inner weights are defined as the simple correlation between latent variables, regardless of whether they function as predictors or responses. This approach resembles traditional factor-analytic logic and tends to distribute influence more evenly across constructs. The inner weight specification for the factor scheme is expressed in Equation (7).

$$v_{ji} = \begin{cases} cor(Y_j, Y_i) & Y_i \text{ and } Y_j \text{ are related} \\ 0 & \text{other} \end{cases} \tag{7}$$

Overall, the key distinction between the two schemes lies in how structural relationships are emphasized. The path scheme explicitly accounts for causal direction and maximizes explained variance in endogenous variables, making it more suitable for predictive and theory-testing purposes. In contrast, the factor scheme emphasizes the overall association structure among latent variables, often resulting in more balanced weight distributions and estimates closer to classical factor analysis [16]. Comparing these two schemes allows for a robustness check of model results and provides deeper insight into how methodological choices influence parameter estimation in PLS-SEM.

iv. Estimation of the structural model.

$$\tilde{Y}_j = \sum_{i=1, i\neq j}^{I} v_{ji} Y_i \tag{8}$$

v. Updating the measurement model weights.

$$\hat{\mathbf{w}}_\mathbf{j} = \left(\tilde{\mathbf{Y}}_\mathbf{j}^\mathbf{T} \tilde{\mathbf{Y}}_\mathbf{j}\right)^{-1} \left(\tilde{\mathbf{Y}}_\mathbf{j}^\mathbf{T} \mathbf{x}_\mathbf{j}\right) \tag{9}$$

vi. Path and loading coefficients estimation.

$$\hat{\boldsymbol{\beta}}_\mathbf{i} = \left(\mathbf{Y}_\mathbf{j}^\mathbf{T} \mathbf{Y}_\mathbf{j}\right)^{-1} \left(\mathbf{Y}_\mathbf{j}^\mathbf{T} \mathbf{Y}_\mathbf{i}\right) \tag{10}$$

$$x_{jh} = \hat{\lambda}_{jh} Y_j \tag{11}$$

$$\hat{\lambda}_{jh} = \hat{\mathbf{w}}_\mathbf{j} = \left(\mathbf{Y}_\mathbf{j}^\mathbf{T} \mathbf{Y}_\mathbf{j}\right)^{-1} \mathbf{Y}_\mathbf{j}^\mathbf{T} \mathbf{x}_\mathbf{j} \tag{12}$$

2.1. Data

This study employed secondary data obtained from the 2022 East Java Health Profile, the 2022 East Java Education Statistics, the 2022 Food Security Index publication, and several datasets released by Statistics Indonesia (BPS) in 2022. The analysis involved five latent variables, each represented by multiple indicators derived from the UNICEF (2021) conceptual framework and several prior studies [7], [17], [18], [19]. A detailed description of the variables used in this study is provided in Table 1.

Table 1. **Research Variables**

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

2.1. Research Procedures

The analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) with a comparison of two weighting schemes, namely the path scheme and the factor scheme, following these steps:

1. Model Specification
   Define the measurement and structural models based on theoretical and empirical considerations, including latent variables, indicators, and hypothesized causal relationships.
2. Data Preparation
   Compile and preprocess secondary data, including data screening and descriptive analysis, to ensure data quality and suitability for PLS-SEM analysis.
3. PLS-SEM Estimation
   Estimate the model using two inner weighting schemes, path and factor, to obtain latent variable scores, outer loadings, and structural path coefficients for each scheme.
4. Measurement Model Evaluation
   Assess indicator reliability and construct validity under both schemes using outer loadingsand Composite Reliability.
5. Structural Model Evaluation
   Evaluate structural relationships for each scheme by examining path coefficients, coefficients of determination (R^2), predictive relevance (Q^2), and Goodness of Fit (GoF), supported by bootstrapping.
6. Comparison of Weighting Schemes and Interpretation
   Compare results from the path and factor schemes to assess the consistency and robustness of indicator contributions, explanatory power, and overall model

performance. Interpret the final results based on the comparative evaluation of both weighting schemes.

3. RESULTS AND DISCUSSION

3.1. Measurement Model Evaluation

PLS-SEM was employed to identify valid and reliable indicators for the latent constructs in the child malnutrition model of East Java Province, with the measurement model evaluation conducted as the first analytical stage.

Table 2. Loading Factor for Each Valid Indicator (Path Scheme)

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

Table 3. Loading Factor for Each Valid Indicator (Factor Scheme)

Latent Variable	Manifest Variable	Loadings
Socio-Economic	$X_{1.1}$	0.961
	$X_{1.2}$	0.970
Parenting	$Y_{1.1}$	0.893
	$Y_{1.2}$	0.504
	$Y_{1.3}$	0.542
Food Security	$Y_{2.1}$	1.000
Health and Environmental Services	$Y_{3.6}$	0.866
	$Y_{3.7}$	0.810
Malnutrition Status	$Y_{4.1}$	0.966
	$Y_{4.2}$	0.754
	$Y_{4.3}$	0.956

Based on the results presented in Table 2 (Path Scheme), the socio-economic construct is mainly represented by Average Years of Schooling ($X_{1.2}$), which has the highest loading factor, indicating that education is the most dominant dimension of socio-economic conditions. For the parenting construct, Exclusive Breastfeeding ($Y_{1.1}$) shows the strongest contribution, highlighting its key role in explaining parenting practices related to child nutrition. Food Security ($Y_{2.1}$) is perfectly represented by the food security index, while Access to Proper Sanitation ($Y_{3.6}$) emerges as the most influential indicator within the health and environmental services construct. In addition, Prevalence of Underweight ($Y_{4.3}$) has the highest loading among malnutrition indicators, suggesting that it most strongly reflects the malnutrition status construct.

A comparison between Table 2 (Path Scheme) and Table 3 (Factor Scheme) shows generally consistent indicator dominance across most latent variables, particularly for socio-economic, food security, and malnutrition status constructs. However, differences are observed in the parenting and health and environmental services constructs, where loading values in Table 3 tend to be more evenly distributed and slightly lower than those in Table 2. This indicates that the path scheme emphasizes indicators with stronger structural influence, whereas the factor scheme captures a more balanced contribution of indicators in representing each latent construct.

Table 4. Reliability Evaluation with Composite Reliability

Latent Variable	Path Scheme	Factor Scheme
Socio-Economic	0.965	0.965
Parenting	0.797	0.694
Food Security	1.000	1.000
Health and Environmental Services	0.739	0.825
Malnutrition Status	0.932	0.924

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. Based on the composite reliability results presented in Table 4, all latent variables demonstrate adequate internal consistency under both the path and factor schemes. The socio-economic and food security constructs show identical and very high reliability values across the two schemes, indicating stable and consistent measurement. The parenting construct exhibits a higher reliability in the path scheme, while in the factor scheme its value (0.694) is very close to the recommended threshold of 0.70 and is therefore considered acceptable and reliable. Notable differences are observed in the health and environmental services construct, which shows higher reliability under the factor scheme than the path scheme, whereas malnutrition status presents slightly higher reliability in the path scheme. Overall, these results suggest that while both schemes provide reliable measurements, the factor scheme improves reliability for certain constructs, whereas the path scheme yields more consistent results for others.

3.2. Structural Model Evaluation

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 [20].

Table 5. Model Determination Coefficient (R^2) Value

Latent Variable	Path Scheme	Factor Scheme
Parenting	0.181	0.162
Food Security	0.524	0.524
Health and Environmental Services	0.487	0.448
Malnutrition Status	0.090	0.229

Based on Table 5, the coefficient of determination (R^2) indicates varying explanatory power across latent variables under both the path and factor schemes. For parenting, the R^2 value is relatively low in both schemes, with the path scheme (0.181) explaining slightly more variance than the factor scheme (0.162), suggesting limited influence of the explanatory variables. Food security shows a moderate and identical R^2 value (0.524) in both schemes, indicating that 52.4% of its variance is consistently explained by the model. In contrast, health and environmental services exhibits a higher R^2 under the path scheme (0.487) compared to the factor scheme (0.448), implying stronger explanatory power in the path-based estimation. Notably, for malnutrition status, the factor scheme yields a substantially higher R^2 (0.229) than the path scheme (0.090), indicating that the factor scheme captures a greater proportion of variance in child malnutrition, although a large share of variability remains explained by factors outside the model in both schemes.

Table 6. Structural Model Evaluation

Statistics Criteria	Path Scheme	Factor Scheme
Q^2 Predictive Relevance	0.818	0.830
Goodness of Fit	0.471	0.515

Following the assessment of the measurement and structural relationships, the structural model was further evaluated to examine its predictive capability and overall model fit, as presented in Table 6. The Q^2 predictive relevance values for both the path scheme (0.818) and the factor scheme (0.830) are substantially greater than zero, indicating that the model has strong predictive relevance in explaining the endogenous latent variables. The slightly higher Q^2 value obtained under the factor scheme suggests a marginally better predictive performance compared to the path scheme. In addition, the Goodness of Fit index was used to assess the overall adequacy of the structural model. The GoF value of 0.471 for the path scheme and 0.515 for the factor scheme both exceed the threshold of 0.36, indicating a strong model fit. Notably, the factor scheme yields a higher GoF value, reflecting a better combined performance of the measurement and structural components. Overall, while both schemes demonstrate strong predictive relevance and good model fit, the factor scheme shows a slightly superior structural model performance.

3.3. Parameter Estimation of Measurement Model and Structural Model

This subsection presents the parameter estimation results for both the measurement model and the structural model. The estimation process was carried out using two different weighting schemes, namely the path scheme and the factor scheme.

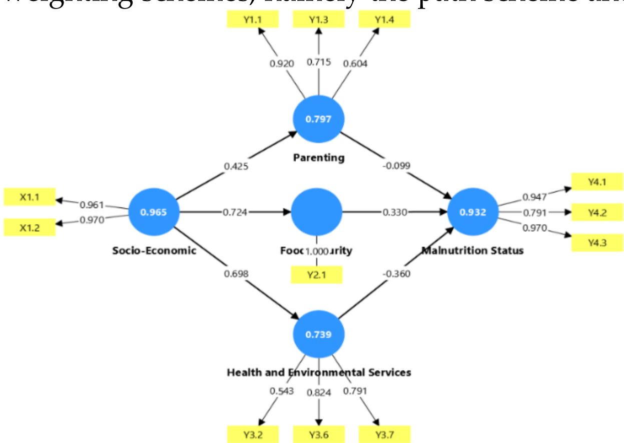

Figure 1. Diagram and Coefficient Values of PLS Model (Path Scheme)

Based on the structural model parameter coefficients presented in Figure 1, the structural model for path scheme can be formulated in Equations (13) – (16).

$$\eta_1 = 0.425\xi_1 + \zeta_1 \tag{13}$$

$$\eta_2 = 0.724\xi_1 + \zeta_2 \tag{14}$$

$$\eta_3 = 0.698\xi_1 + \zeta_3 \tag{15}$$

$$\eta_4 = -0.099\eta_1 + 0.33\eta_2 - 0.36\eta_3 + \zeta_4 \tag{16}$$

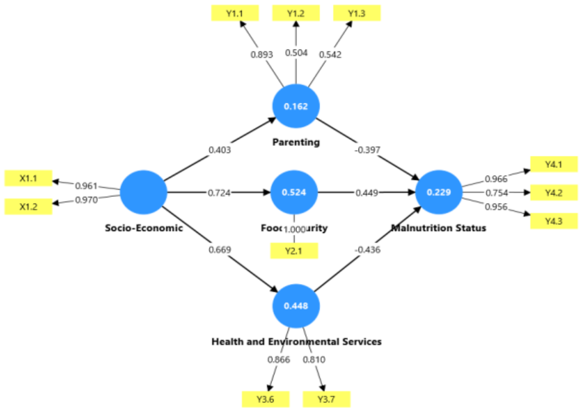

Figure 2. Diagram and Coefficient Values of PLS Model (Factor Scheme)

Based on the structural model parameter coefficients presented in Figure 2, the structural model for factor scheme can be formulated in Equations (17) – (20).

$$\eta_1 = 0.403\xi_1 + \zeta_1 \tag{17}$$

$$\eta_2 = 0.724\xi_1 + \zeta_2 \tag{18}$$

$$\eta_3 = 0.669\xi_1 + \zeta_3 \tag{19}$$

$$\eta_4 = -0.397\eta_1 + 0.449\eta_2 - 0.436\eta_3 + \zeta_4 \tag{20}$$

3.4. Hypothesis Testing of Measurement Model and Structural Model

After completing the estimation and evaluation of the measurement and structural models, hypothesis testing was performed using the parameter estimates obtained from both models. The tested parameters included λ, γ, and β, with statistical significance assessed through a bootstrap resampling procedure involving 5,000 iterations. Within the PLS-SEM framework, hypothesis decisions were based on the corresponding t-statistics derived from the bootstrap results.

Table 7. Measurement Model Testing Results with Resampling Bootstrap (Path Scheme)

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

Table 8. Measurement Model Testing Results with Resampling Bootstrap (Factor Scheme)

Latent Variable	Manifest Variable	Loadings	T-Statistics	P-value	Information
Socio-Economic	$X_{1.1}$	0.961	84.305	0.000	Valid, significant
	$X_{1.2}$	0.970	142.719	0.000	Valid, significant
Parenting	$Y_{1.1}$	0.893	4.274	0.000	Valid, significant
	$Y_{1.2}$	0.504	1.049	0.294	Valid, not significant
	$Y_{1.3}$	0.542	1.412	0.158	Valid, not significant
Food Security	$Y_{2.1}$	1.000	*	*	

Health and Environmental Services	$Y_{3.6}$	0.866	14.220	0.000	Valid, significant
	$Y_{3.7}$	0.810	7.227	0.000	Valid, significant
Malnutrition Status	$Y_{4.1}$	0.966	6.398	0.000	Valid, significant
	$Y_{4.2}$	0.754	4.387	0.000	Valid, significant
	$Y_{4.3}$	0.956	7.521	0.000	Valid, significant

Based on the results in Table 7 (path scheme) and Table 8 (factor scheme), the measurement model generally shows good indicator validity, as most indicators have statistically significant loading factors (t-statistic > 1.96). Under the path weighting scheme, all indicators are significant, indicating that each manifest variable reliably measures its corresponding latent construct. In contrast, under the factor weighting scheme, two indicators of the parenting construct are not statistically significant, suggesting weaker contributions when estimation emphasizes correlations rather than directional relationships. Overall, the comparison indicates that the path scheme yields more stable and robust measurement results, while the factor scheme is more sensitive to indicator strength, highlighting the importance of evaluating alternative weighting schemes in PLS-SEM.

Table 9. Structural Model Testing Results with Resampling Bootstrap (Path Scheme)

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

Table 10. Structural Model Testing Results with Resampling Bootstrap (Factor Scheme)

Path	Coefficient	T-Statistics	P-value
Socio-Economic → Parenting	0.403	2.305	0.021
Socio-Economic → Food Security	0.724	10.409	0.000
Socio-Economic → Health and Environmental Services	0.669	10.928	0.000
Parenting → Malnutrition Status	-0.397	1.178	0.239
Food Security → Malnutrition Status	0.449	1.684	0.092
Health and Environmental Services → Malnutrition Status	-0.436	1.978	0.048

Based on the structural model results under both weighting schemes, socio-economic conditions consistently show a significant positive effect on parenting, food security, and health and environmental services. Under the path scheme, the effects of socio-economic factors on parenting ($\beta = 0.425$, $p = 0.007$), food security ($\beta = 0.724$, $p < 0.001$), and health and environmental services ($\beta = 0.698$, $p < 0.001$) are all statistically significant, and similar magnitudes and significance are observed under the factor scheme ($\beta = 0.403$, $\beta = 0.724$, and $\beta = 0.669$, respectively). In contrast, both schemes consistently indicate that parenting and food security do not have a significant direct effect on malnutrition status, although the factor scheme yields slightly larger coefficients for these paths. Importantly, health and environmental services exhibit a significant negative effect on malnutrition status in both schemes, with comparable t-statistics just above the critical threshold, indicating that improvements in these services are associated with reductions in child malnutrition. Overall, while the direction and significance of key relationships are largely consistent across schemes, the factor scheme tends to produce slightly different coefficient magnitudes, underscoring the value of comparing weighting schemes to assess the robustness of structural conclusions in PLS.

4. CONCLUSION

PLS-SEM results demonstrate that both the path and factor weighting schemes are effective for modeling child malnutrition in East Java, as evidenced by generally acceptable measurement and structural model performance. Under the path scheme, all indicators in the measurement model show statistically significant loadings, confirming strong indicator validity and reliability. In contrast, the factor scheme yields several indicators with non-significant loadings, particularly within the parenting construct, indicating that this scheme is more sensitive to weaker indicator–construct relationships. These differences suggest that the path scheme provides a more robust measurement model when the primary objective is to ensure strong indicator significance and explanatory consistency, whereas the factor scheme offers a more conservative assessment of indicator contributions.

From a structural perspective, both schemes produce consistent substantive conclusions. Socio-economic factors have a stable and significant positive influence on parenting, food security, and health and environmental services, while parenting and food security do not exert significant direct effects on malnutrition status. Importantly, health and environmental services show a significant negative effect on malnutrition status under both schemes, highlighting their critical role in reducing child malnutrition. Although the factor scheme generates slightly different coefficient magnitudes and marginal significance levels, the direction and overall interpretation of the relationships remain stable across schemes. Taken together, these findings indicate that the path scheme is preferable for prediction-oriented and explanatory modeling, while the factor scheme is valuable for robustness checks, as it helps identify weaker indicators and assess the sensitivity of results to alternative weighting assumptions in PLS-SEM.

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Author Contributions Statement

Zulfani Alfasanah: Validation, Visualization, Conceptualization, Methodology, Software, Writing - Original draft. **Bambang Widjanarko Otok:** Conceptualization, Methodology, Validation, Supervision, Writing - reviewi & editing. **Muhammad Ahsan:** Conceptualization, Methodology, Validation, Supervision, Writing - reviewi & editing.

Conflict of Interest Statement

Authors state no conflict of interest.

Informed Consent

None

Ethical Approval

None

Data Availability

The dataset is openly available at the following link: https://dinkes.jatimprov.go.id/userfile/dokumen/PROFIL%20KESEHATAN%20JATIM%202022.pdf

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