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A Thematic Mapping Approach to Segmentation Stunting in Indonesia by Province Using Finite Mixture Partial Least Square Method

Ayu Setya Permatasari¹, Rahmawati Erma Standsyah²

¹Student of Department of Mathematics, Faculty of Mathematics and Natural Sciences, Universitas Negeri Surabaya, Surabaya, Indonesia

²Department of Mathematics, Faculty of Mathematics and Natural Sciences, Universitas Negeri Surabaya, Surabaya, Indonesia

Abstract

Stunting remains one of Indonesia's most persistent public-health problems, and the national prevalence figure hides substantial variation across the country's 38 provinces. This study models six latent constructs behind childhood stunting antenatal care, early initiation of breastfeeding, immunization, sanitation, exclusive breastfeeding, and low birth weight using Partial Least Squares Structural Equation Modeling on 2023-2024 provincial health-profile data published by Indonesia's Ministry of Health, and then applies Finite Mixture Partial Least Squares (FIMIX-PLS) to detect unobserved heterogeneity across provinces and to translate the resulting segments into a thematic map. The measurement model satisfied every recommended validity and reliability threshold, with an Average Variance Extracted between 0.835 and 0.932 and both Cronbach's alpha and composite reliability above 0.80. In the pooled national model, antenatal care and low birth weight were the only two constructs with a statistically significant direct path to stunting ($\beta = -0.487$ and 0.540 , respectively; $p < 0.001$), together explaining 63.0% of the variance in stunting. Model-selection criteria favored a three-segment solution comprising 21, 10, and 7 provinces, dominated respectively by sanitation-related, birth-weight-related, and breastfeeding-related structural pathways. Mapping these segments geographically shows that provinces sharing a dominant pathway are not scattered at random but tend to cluster by region, indicating that stunting-reduction programs should be tailored to each segment's dominant pathway rather than applied uniformly across the whole country.

Keywords: FIMIX-PLS; SEM-PLS; stunting; thematic map

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1. Introduction

Stunting is one of those problems that never has a single cause. Stunted growth means the height of a child being very small compared to their peers. But the root cause behind this issue is generally associated with the most crucial period of one's life – 1,000 days after birth [1]. Analyzing the statistics of different countries, we have noticed the constant tendency, as if this same thing was happening everywhere. It is not just "lack of nutrition", it is something deeper and much more complicated; it is something similar to the chain reaction: poor health care, poor nutrition, and poor environment – all these factors combined during this crucial period [2], [3].

*Corresponding author. E-mail: xxxxx@xxxxx.com

The most shocking aspect of this case is not merely the children's shorter physical stature. The impact of this nutritional deficiency will affect them throughout their lives: cognitive limitations, brain development issues, and an increased risk infancy resurfaces decades later as a burden on the person and on the health system that has to treat them [4].

Indonesia carries more of that burden than is middle-income status world suggest. The 2023 Indonesia Health Survey put national stunting prevalence at 21.5%, barely down from 21.6% the year before [5], still above the 14% government target and above the 20% mark the World Health Organization treats as a public-health alarm [6]. That national number also hides a lot Papua Tengah, Nusa Tenggara Timur, and Papua Pegunungan sit at the top of the 2023 rankings, part of Java and Bali stay comfortably below the national average, and more than half of Indonesia's 38 provinces are still above it [5], [7]. Some of the inequalities come from differences in money and opportunities for work. Family income and jobs matter a lot too. The schooling the mothers got is another factor [8], [9]. These all play into what food or medical care or sanitation the family can get and it varies by region. If just one thing stood out then the rates should be equal everywhere but they are not. That points to something else being involved. This suggests there might be more going on than what shows up at first [10].

All of the above cannot be measured directly through any standard. Quality of health care services and environmental sanitation are examples of latent constructs which are inferred from the variables that can be directly observed. This may be one of the reasons why structural equation modeling has gained popularity in recent studies on nutrition among children in Indonesia during the last decade. The modeling approach has been used to analyze malnutrition prevalence in locations such as Aceh[11], as well as for determining the changes in inequalities in stunting in the country [8]. Studies have also been carried out in relation to the association between water and sanitation access and health effects on mothers and children throughout Indonesia. The aspect regarding its popularity quite logical considering that direct measurement is impossible in such situations. However, some may disagree [12]. Studies on the impact of sanitation facilities have identified similar negative correlations between stunting in eastern Indonesia and Papua [13], [14]. Also, there are geographic clusters of vaccination rates associated with regions having higher levels of stunting in the area [15]. The PLS regression analysis technique can be used in this situation since it does not assume the multivariate normal distribution [11].

The problem is that applying one SEM-PLS model to each province while assuming all these provinces as one and same population, which has been contradicted by the above mentioned prevalence gap, is indeed a limitation that has been proved by previous studies on stunting based on clustering [16]. The Finite Mixture Partial Least Square (FIMIX-PLS) model proposed by Hahn et al. [17] and then implemented by Ringle et al. [18], addresses exactly this problem because it estimates both path coefficients and membership probability of segments at the same time.

While there are limited number of studies on applying the technique to analyze Indonesian stunting data, these studies still lack in completeness. Linda and Huda [4] used the technique to classify 34 provinces based on antenatal care, breastfeeding, immunization, and sanitation as the exogenous constructs with the result of 4 segments. However, the authors stopped writing in the middle of their research after presenting the results in table form only. Madeira and Anuraga [10] went finer, down to the district/city level, which is a genuine strength, but they examined only one province, Nusa Tenggara Timur, so there is no sense of how that province compares with the rest of the country. Surayya and Sirait [11] built a solid PLS-SEM model of undernutrition in Aceh, covering health access, food intake, and socioeconomic status, but never added a heterogeneity-detection step, so whatever variation exists within the province is simply averaged into one set of path coefficients. Taken together, these three studies point to a clear gap: no study has combined a national, multi-province structural model of health-service, breastfeeding, immunization, and environmental pathways with a heterogeneity-detection layer and a map that translates the statistical output into something usable for decision-making. This paper aims to fill that space.

This paper contributes in three ways. Methodologically, to the best of our knowledge, this is the first Indonesian stunting study to run outer-model validation, bootstrapped inner-model testing, FIMIX-PLS heterogeneity detection, and thematic mapping as one continuous pipeline rather than

treating segmentation as a separate step bolted on at the end. The structural model itself goes further than the antenatal-care-and-sanitation core used in [4] or the single composite health-access construct used in [10]: early initiation of breastfeeding, immunization, and environmental sanitation are each modeled as their own latent construct alongside antenatal care, exclusive breastfeeding, and low birth weight, producing a fuller six-construct picture of how these pathways interact at the national level. The development of thematic maps from segment membership is a crucial component of the findings and is not merely a decorative addition to the study. The methodologist can find analytical information in segment probability tables, and policy makers who need to quickly determine whether provinces have comparable risk profiles and vulnerabilities can find the same information in shaded maps. The assessment of whether FIMIX-PLS segments fit regional patterns, such as whether there is a distinct cluster for eastern Indonesia, and whether provinces with high prevalence, like Central and Highland Papua, are in fact distinct structural segments, is also made possible by the use of thematic maps. Using segment membership tables to solve these problems is nearly impossible. And this means that there is a dominant structural route for each segment in the provinces. And here we have strategic targeting tools rather than statistical classifications because segments related to antenatal care require a completely different intervention approach from segments linked to sanitation or birth weight. This cannot be achieved by using just one national model. Information can be found in Section 2. Section 2 includes the data and the FIMIX-PLS method, while Section 3 will include the measurement model, the structural model, the bootstrapping output, and finally the segmentation by provinces along with its thematic map.

2. Methods

This research an applied quantitative approach was employed by using secondary data from the province for the purpose of clustering 38 Indonesian provinces in relation to stunting contributing factors patterns. There was no manipulation or control group used, as this research was not about manipulating and measuring any kind of control group. The value this study adds comes from applying Finite Mixture Partial Least Squares (FIMIX-PLS) at national scale, refreshing both the latent variables and the data period along the way, then pushing things one step further by turning the segmentation output into a thematic map visualization, something neither references study got around to doing.

2.1. Research Design and Data

This is an applied, quantitative study built on secondary data, with each of Indonesia's 38 provinces treated as one unit of analysis. What's being modeled is how six latent variables line up to produce stunting: antenatal care (ξ_1), early initiation of breastfeeding (ξ_2), immunization (ξ_3), and environmental sanitation (ξ_4) sit on the exogenous side, while exclusive breastfeeding (η_1), low birth weight (η_2), and stunting (η_3) sit on the endogenous side. Each construct is measured through several manifest indicators pulled from routine health-profile statistics, following the same indicator structure used in comparable FIMIX-PLS stunting studies in Indonesia [4], [10]. The analysis itself runs in three stages: outer model evaluation, inner model evaluation with bootstrap-base hypothesis testing, and finally FIMIX-PLS segmentation, each of which is laid out below with its governing equations.

2.2. Measurement Model (Outer Model)

Every construct in this model is reflective, meaning the indicators are treated as manifestations of the underlying latent variable rather than the other way around. For an exogenous construct ξ_j with indicator x_j and an endogenous construct η_j with indicator y_j , the outer model is written as Eq. (1), (2),

$$x_j = \lambda_j \xi_j + \delta_j \quad (1)$$

$$y_j = \lambda_j \eta_j + \varepsilon_j \quad (2)$$

Where λ_j is the loading factor linking the indicator to its construct, and δ_j, ε_j are the corresponding measurement errors. An indicator is kept in the model only if its loading exceeds 0.6; anything below that is dropped and the model is re-estimated [17].

Convergent validity is then checked through the Average Variance Extracted (AVE) in Eq. (3), where a construct is considered valid once AVE exceeds 0.50,

$$AVE = \frac{\sum_{i=1}^n \lambda_i^2}{(\sum_{i=1}^n \lambda_i^2) + (\sum_{i=1}^n Var(\varepsilon_i))} \quad (3)$$

With λ_i denoting the estimated loading of indicator i and $var(\varepsilon_i)$ its measurement-error variance. Reliability is checked two ways: composite reliability, ρ_c , in Eq. (4), both of which should sit above 0.70 for a construct to be considered internally consistent [10].

$$\rho_c = \frac{(\sum_{i=1}^n \lambda_i)^2}{(\sum_{i=1}^n \lambda_i)^2 + \sum_{i=1}^n Var(\varepsilon_i)} \quad (4)$$

$$\alpha = \frac{n}{n-1} \left(1 - \frac{\sum_{i=1}^n S_i^2}{S_t^2} \right) \quad (5)$$

Where n is the number of indicators for a construct, S_t^2 is the total variance across those indicators, and S_i^2 is the variance of indicator i

2.3. Structural Model (Inner Model)

The outer model clears validity and reliability, the structural relationship among the seven latent constructs are estimated as Eq. (6),

$$\eta_j = \sum_{i=1}^I \beta_{ji} \eta_i + \sum_{b=1}^B \gamma_{jb} \xi_b + \zeta_j \quad (6)$$

Where β_{ji} is the path coefficient linking endogenous construct η_i to η_j , γ_{jb} is the path coefficient linking exogenous construct ξ_b to η_j , and ζ_j is the structural error term. Model fit is read from the coefficient of determination, R^2 , computed as Eq. (7),

$$R^2 = 1 - \frac{\sum_{i=1}^n (Y_i - \hat{Y}_i)^2}{\sum_{i=1}^n (Y_i - \bar{Y})^2} \quad (7)$$

With Y_i the observed value of the endogenous construct, $\hat{Y}_i$ its model-predicted value, and $\bar{Y}$ its mean: an R^2 Of 0.75, 0.50, and 0.25 is conventionally read as substantial, moderate, and weak, respectively [19]. Because PLS has no closed-form standard error, the significance of each path is instead tested through bootstrap resampling, with the t-statistic in Eq. (8),

$$T_{value} = \frac{b_j}{S(b_j)} \quad (8)$$

Where b_j is the bootstrapped estimate of path coefficient γ_j and $S(b_j)$ is its bootstrap standard error; a path is treated as significant at the 5% level once the two-tailed p-value from 500 bootstrap resamples falls below 0.05 [11].

2.4. FIMIX-PLS Segmentation

The structural model above is fitted once across all 38 provinces, which silently assumes they behave as a single homogeneous population. FIMIX-PLS relaxes that assumption by treating the endogenous construct scores as drawn from a finite mixture of K latent segments, following Eq. (9),

$$\eta_m \sim \sum_{k=1}^K \rho_k f(m|k)(\eta_m | \xi_m, B_k, \Gamma_k, \Psi_k) \quad (9)$$

Where ρ_k is the mixing proportion of segment k ($\rho_k > 0$, $\sum_{k=1}^K \rho_k = 1$), and $f_{m|k(\cdot)}$ is the conditional multivariate normal density of case m given segment k , parameterized by the segment-specific path-coefficient matrices B_k and Γ_k and the residual-variance matrix Ψ_k [17], [20]. The mixture is estimated via an EM algorithm that alternates between computing each province's posterior segment-membership probability and re-estimating the segment-specific path coefficients until convergence [18].

Because the number of segments K is not known beforehand, several candidate values ($K = 2, 3, 4, \dots$) are compared using four criteria: the Akaike Information Criterion in Eq. (10), the Bayesian Information Criterion in Eq. (11), the Consistent AIC in Eq. (12), and the Normed Entropy in Eq. (13) [7],

$$AIC_k = -2 \ln L + c N_k \quad (10)$$

$$BIC_k = -2 \ln L + \ln N_k \quad (11)$$

$$CAIC_k = -2 \ln L + (\ln(M) + 1) N_k \quad (12)$$

$$EN = 1 - \frac{\sum_{m=1}^M \sum_{k=1}^K P_{mk} \ln(P_{mk})}{M \ln(K)} \quad (13)$$

Where L is the model likelihood, q_k is the number of free parameters for segment solution k , N is the number of observations, M is the number of provinces, K is the number of segments, and P_{mk} is the estimated probability that province m belongs to segment k . Lower AIC, BIC, and CAIC indicate a better-fitting segmentation, while EN closer to 1 indicates cleaner separation between segments; the K that best satisfies all four is retained as the final segmentation [21].

SmartPLS was used for the SEM-PLS estimation, the bootstrapping procedure, and the FIMIX-PLS segmentation, with 500 bootstrap subsamples for hypothesis testing, in line with standard practice in PLS-based stunting research [4], [10]. After finding the best value of K , each province is classified to the group having the highest P_{mk} value and the resulting groups are shown on a thematic map, each group corresponding to a color linked to the dominant structural pathway of each group. Therefore, the final segmentation is obtained by two concurrent criteria: the statistical criteria in Eqs. (10)–(13) for the selection of K and the possibility to substantially interpret the dominant path of each segment [21].

3. Results and Discussion

The data used in this study are secondary data obtained from the Ministry of Health of the Republic of Indonesia (Kemenkes RI), specifically the 2023-2024 health-profile publication, which reports several indicators tied to the causes of stunting across Indonesia's provinces. The dataset is publicly accessible through the ministry's official website, kemenkes.go.id. Table 1 lists the latent variables and indicators used in this study.

Table 1: Research variables and indicator

Latent Variabel	Indicator	Description
Antenatal Care	X_{11}	Percentage of pregnant women receiving antenatal care every trimester, four visits within one year, from a health worker (K4)
	X_{12}	Percentage of pregnant women receiving antenatal care six visits within one year, from a health worker (K6)
Sanitation	X_{21}	Percentage of households with access to proper sanitation
	X_{22}	Percentage of households with access to proper drinking-water facilities
	X_{23}	Percentage of village practicing open-defecation-free sanitation
Immunization	X_{31}	Percentage of infants who received complete basic immunization
	X_{32}	Percentage of infants who received DPT/HB immunization
	X_{33}	Percentage of infants who received the polio vaccine
	X_{34}	Percentage of infants who received the measles vaccine
Early Initiation of Breastfeeding	X_{41}	Percentage of infants who began breastfeeding immediately after birth (IMD)
Exclusive Breastfeeding	Y_{11}	Percentage of infants who received exclusive breastfeeding for 6 months without any additional food or drink
Low Birth Weight	Y_{22}	Percentage of babies born with low birth weight (<2.500 gram)
Stunting	Y_{31}	Proportion of children with stunting
	Y_{32}	Proportion of children with wasting

3.1. Measurement Model Evaluation

The outer model was checked on two counts before any path got interpreted. Convergent validity came first, judged by each indicator's outer loading, kept only above 0.6, and by each construct's Average Variance Extracted (AVE), accepted once above 0.50. Reliability came second, checked through Cronbach's alpha, and composite reliability (ρ_c), all expected to clear 0.70 [17]. Any indicator that failed the loading cutoff was dropped and the model re-estimated before the structural stage began.

Fig. 1: Path diagram of the stunting SEM-PLS model

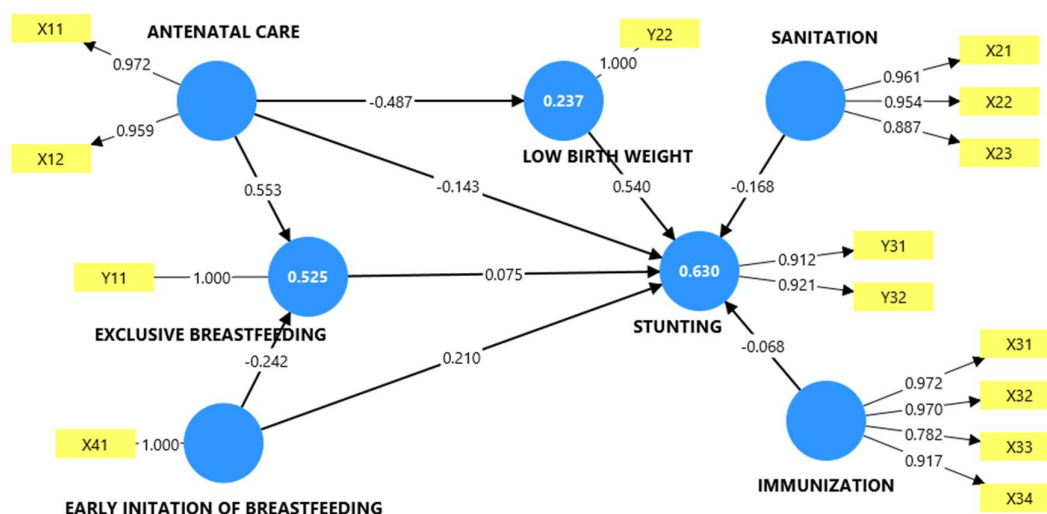


Fig. 1 shows the path diagram that survived that cut. Antenatal care's two indicators, X_{11} and X_{12} , load at 0.972 and 0.959; sanitation's three indicators, X_{21} through X_{23} , sit between 0.887 and 0.961; immunization's four indicators, X_{31} through X_{34} , range from 0.782 to 0.972; stunting is carried by two indicators, Y_{31} and Y_{32} , loading at 0.912 and 0.921; and early initiation of breastfeeding, exclusive breastfeeding, and low birth weight are each measured by a single indicator loading at exactly 1.000, as expected for a single-item construct. Every retained indicator clears the 0.6 convergent-validity bar typically applied in SEM-PLS stunting research [4], [11].

Table 2 carries the validity and reliability check through to the construct level. Antenatal care, immunization, and sanitation are multi-item constructs, so their AVE, alpha, composite reliability (ρ_c) can all be computed; stunting is a two item construct and follows the same logic; early initiation of breastfeeding, exclusive breastfeeding, and low birth weight are single-item constructs, so their reliability is fixed by construction (loading = 1.000) and SmartPLS does not report a separate coefficient for them.

Table 2: Construct reliability and convergent validity

Construct	AVE	Cronbach's Alpha	Composite Reliability
Antenatal Care	0.932	0.928	0.965
Immunization	0.835	0.932	0.952
Sanitation	0.874	0.927	0.954
Stunting	0.840	0.810	0.913

All multi-item construct in Table 2 clears both bars at once: AVE runs from 0.835 to 0.932, well above then 0.50 floor, and Cronbach's Alpha, Composite Reliability all sit above 0.80, comfortably above the 0.70 floor. Stunting posts the lowest AVE and Cronbach's Alpha of the four, 0.840 and 0.810, which still leaves it well inside the acceptable range; it's simply the construct with the most indicator-to-indicator variation to explain, since Y_{31} and Y_{32} capture two related but not identical severity bands of the same outcome. The measurement model, in short, gives no reason to doubt any construct's validity or reliability, which means the structural results that follow are being read off a fairly solid outer model.

Collinearity among the indicators of the same construct was also inspected, since indicators of a reflective construct are expected to be highly correlated with one another; the outer-model VIF values ranged from 1.00 for the single-indicator constructs up to 14.78 for X_{31} , a pattern that is unremarkable for reflective blocks and does not by itself indicate a specification problem. What matters more for interpreting the structural model is collinearity among the exogenous constructs that jointly predict the same endogenous construct: the inner-model VIF for antenatal care as a predictor of stunting is 6.55, noticeably higher than the VIF of the other five predictors of stunting, which cluster between 1.70 and 4.04. This reflects the fact that antenatal care correlates strongly with both immunization and sanitation at the province level.

The measurement model met every recommended evaluation criterion, covering indicator reliability, convergent validity, internal consistency reliability, and an acceptable collinearity profile. The subsequent structural relationships can therefore be interpreted with adequate confidence on the back of these results. Still, the relatively higher VIF value for antenatal care needs to be kept in mind when interpreting its direct and indirect effects in the next structural model analysis.

3.2. Structural Model Evaluation

With the outer model confirmed as valid and reliable, the structural relationships among the

seven latent constructs in Eq. (6) were estimated next, and their explanatory power was read from the coefficient of determination (R^2) in Eq. (7). Table 4 reports R^2 for the three endogenous constructs: exclusive breastfeeding, low birth weight, and stunting. Following the conventional benchmarks of 0.75, 0.50, and 0.25 for substantial, moderate, and weak explanatory power [19], the model explains stunting and exclusive breastfeeding at a moderate level and low birth weight at a level closer to weak, meaning that a meaningful share of the variation across provinces in low birth weight still traces back to factors outside the four exogenous constructs considered here.

Table 3: Coefficient of determination (R^2) of the endogenous constructs

Endogenous Construct	R^2
Exclusive Breatfeeding	0.525
Low Birth Weight	0.237
Stunting	0.630

The model explains 63.0% of the variance in stunting ($R^2 = 0.630$), which lands in the moderate-to-substantial range; 52.5% in exclusive breastfeeding ($R^2 = 0.525$), also moderate; and 23.7% in low birth weight ($R^2 = 0.237$), which counts as weak on its own but still means almost a quarter of provincial variation in birth weight traces back to antenatal care alone. Table 3 describes the nine structural pathways in terms of the second criterion, now with exact t-statistics and p-values from the bootstrap, no longer integers read from the graph.

As there are no analytical expressions of the standard errors of PLS, the statistical significance of the paths was assessed using bootstrapping with 500 samples, in accordance with the Eq. (8), the two-sided t-statistics and p-values of the parameters are reported in Table 4, along with the implied fit measures of the model. The fit of the model is satisfactory: the mean root standardized residual (MRSR) of the estimated model is 0.080 and the normalized fit index (NFI) is 0.719 all those numbers are within the acceptable range for composite PLS models of that size [19].

Table 4: Path coefficients and bootstrap significance testing

Structural path	Coefficient	Standar Error	t-statistic	p-value	Result ($\alpha = 0.05$)
Antenatal Care → Exclusive Breastfeeding	0.553	0.157	3.523	0.0004	Significant
Antenatal Care → Low Birth Weight	-0.487	0.130	3.758	0.0002	Significant
Antenatal Care → Stunting	-0.143	0.345	0.415	0.678	Not significant
Early Initiation of Breastfeeding → Exclusive Breastfeeding	-0.242	0.171	1.414	0.157	Not significant
Early Initiation of Breastfeeding → Stunting	0.210	0.174	1.207	0.228	Not significant
Exclusive Breastfeeding → Stunting	0.075	0.202	0.370	0.712	Not significant
Immunization → Stunting	-0.068	0.202	0.338	0.735	Not significant
Low Birth Weight → Stunting	0.540	0.147	3.662	0.0003	Significant
Sanitation → Stunting	-0.168	0.279	0.602	0.547	Not significant

Only three of the nine hypothesized paths are sustained at the 5 per cent level. Antenatal care pushes exclusive breastfeeding up significantly ($\beta = 0.553$, $t = 3.523$, $p < 0.001$), and it pulls low birth weight down just as significantly ($\beta = -0.487$, $t = 3.758$, $p < 0.001$). This tracks with what other research has already shown regular antenatal contact seems to lower low-birth-weight risk, mostly by keeping closer tabs on maternal nutrition and catching pregnancy complications sooner Low birth weight,

in turn, drives stunting up significantly ($\beta = 0.540$, $t = 3.662$, $p < 0.001$), which fits with earlier Indonesian work naming low birth weight as one of the steadier individual-level predictors of stunting [22].

Here's the Interesting although antenatal care, immunization, and sanitation are commonly regarded as key interventions for reducing stunting, none of these variables shows a statistically significant direct effect on stunting once the structural model is estimated simultaneously ($p = 0.678$, 0.735 , and 0.547 , respectively). Likewise, the direct effects of early initiation of breastfeeding and exclusive breastfeeding also fall well short of statistical significance. Therefore, the hypotheses proposing direct effects of early initiation of breastfeeding, immunization, sanitation, and exclusive breastfeeding on stunting were not supported in the pooled national model. Instead, these results in addition to the high VIF of 6.55 for antenatal care on the model internal level may imply that the impact of these practices on stunting occurs indirectly via low birth weight and exclusive breastfeeding.

Two potential explanations stand out in connection with the results on breastfeeding. Early initiation of breastfeeding is a discrete variable that stands for a single event that happened during the first hour after delivery as opposed to an ongoing practice. Lack of association between early initiation and exclusive breastfeeding ($p = 0.157$) or stunting ($p = 0.228$) demonstrates that early initiation cannot be used as a predictor of future behaviors. A likely explanation is that the continuation of breastfeeding depends on factors such as maternity leave policies, family support, and exposure to infant formula marketing—factors not accounted for in this model. The absence of a significant relationship between exclusive breastfeeding and stunting ($p = 0.712$) is harder to reconcile with the protective effects observed at the individual level in other studies; however, at the provincial level, these effects may be mitigated by conditions prevailing after the age of six months. Two provinces with identical breastfeeding coverage rates could exhibit vastly different rates of stunting if the quality of complementary feeding differs—an aspect that falls outside the scope of the four exogenous constructs modeled here.

Immunization and sanitation operate according to interdependent yet distinct logics. The non-significant direct link observed for vaccination ($p = 0.735$) can be plausibly explained from a clinical perspective: vaccines primarily protect against morbidity and mortality associated with acute infectious diseases, whereas the link to chronic linear growth retardation involves a longer, indirect chain—where reduced infection frees up energy for growth—that is difficult to detect through simple cross-sectional analysis, especially after accounting for the shared variance among vaccination, prenatal care, and sanitation (as evidenced by the previously noted high VIF value of 6.55). The non-significant combined link regarding sanitation ($p = 0.547$) proves to be the model's most informative null result: demonstrates that the impact of sanitation on growth retardation is strongly negative in a segment comprising more than half of the provinces ($\beta = -0.898$) but much weaker in the other regions; thus, the combined coefficient represents an average between a real, pronounced impact in certain provinces and a negligible impact in others. In other words, a non-significant combined link does not imply that the construct lacks importance; on the contrary, it may reveal inter-provincial heterogeneity—the very type of variation the FIMIX-PLS method is designed to highlight—which serves as the basis for the subsequent segmentation analysis.

To test whether that explanation actually holds up, the specific indirect effects running through low birth weight and exclusive breastfeeding were bootstrapped separately, with results shown in Table 5.

Table 5: Spesific indirect effects

Indirect path	Coefficient	t-statistic	p-value	Result ($\alpha = 0.05$)
Antenatal Care → Low Birth Weight → Stunting	-0.263	2.297	0.022	Significant
Antenatal Care → Exclusive Breastfeeding → Stunting	0.041	0.345	0.730	Not significant
Early Initiation of Breastfeeding → Exclusive Breastfeeding → Stunting	-0.018	0.294	0.769	Not significant

This describes a fully mediated relationship: antenatal care does not move stunting directly so much as it lowers the risk of low birth weight, and it is low birth weight that actually drives stunting down. Combining the direct and indirect effects gives antenatal care a total effect on stunting of -0.365 larger in magnitude than its non-significant direct effect alone, and the clearest evidence that antenatal care matters for stunting chiefly by improving birth weight rather than through some other unmodeled channel. Immunization and sanitation, by contrast, showed neither a significant direct effect nor a route through either significant mediator, consistent with their comparatively small effect sizes ($f^2 = 0.004$ and 0.019 , respectively, against 0.464 for the low birth weight to stunting path) and suggesting their independent contribution to explaining cross-province variation in stunting is limited relative to birth weight.

The estimated structural model can be summarized in three equations, one per endogenous construct:

$$\begin{aligned}\eta_1 &= 0.553\xi_1 - 0.242\xi_2 + \zeta_1 \\ \eta_2 &= -0.487\xi_1 + \zeta_2 \\ \eta_3 &= -0.143\xi_1 + 0.210\xi_2 - 0.068\xi_3 - 0.168\xi_4 + 0.075\eta_1 + 0.540\eta_2 + \zeta_3\end{aligned}$$

Model fit was acceptable overall: SRMR for the estimated model was 0.080 (against 0.054 for the saturated model) and NFI was 0.719, both within ranges commonly treated as tolerable for a composite-based PLS model of this size, though the SRMR sits right at the conventional 0.08 ceiling and is worth flagging rather than glossing over. Two immunization indicators X_{31} and X_{32} , also carried a variance inflation factor above 10 (14.78 and 14.30, respectively), pointing to appreciable collinearity between BCG and measles coverage rates an unsurprising pairing, since provinces that vaccinate well against one disease tend to vaccinate well against the other, but a limitation worth naming when interpreting immunization's own non-significant path to stunting.

3.3. FIMIX-PLS Segmentation and Thematic Mapping

The structural model estimated above pools all 38 provinces into a single population, which implicitly assumes they share one common set of path coefficients. FIMIX-PLS was applied to test that assumption directly, following Eq. (9)-(13), by comparing candidate segment solutions $K = 2$ through $K = 5$, each estimated with 5000 maximum iterations and 10 repetitions under a fixed seed to guard against local optima. Table 6 reports the resulting model-selection statistics for every candidate K .

Table 6: FIMIX-PLS model selection criteria for $K = 2$ to $K = 5$

Criterion	K = 2	K = 3	K = 4	K = 5
AIC	257.293	215.617	202.770	172.776
BIC	298.233	277.845	286.287	277.582
CAIC	323.233	315.845	337.287	341.582
EN	0.771	0.981	0.957	0.972

Read AIC on its own and it looks like more segments are always better, it keeps dropping all the way to $K = 5$. This is a well-known feature of the AIC criterion in mixed models: it almost entirely ignores the additional complexity increase and favors the highest possible K value [21]. The results produced by the CAIC and EN criteria are much shorter. Specifically, in terms of CAIC criterion, the minimum is observed at $K = 3$ (315.845); for values of $K = 4$ and $K = 5$, it starts growing again; in turn, EN criterion exhibits a maximum at $K = 3$ (0.981), which is the closest value to the optimal one and is noticeably higher than 0.771, which is regarded as a mediocre value at $K = 2$. Difference between BIC criterion values for $K = 3$ (277.845) and $K = 5$ (277.582) is absolutely insignificant: just two tenths of a point. Overall, especially taking into account the CAIC and EN criteria, which have proven their ability to restrain the tendency of AIC criterion to exaggerate the number of segments [21], $K = 3$ can

be regarded as the most appropriate segmentation: As it is clear, it is noticeably better than that of CAIC and EN criteria and statistically indistinguishable from the preferred by AIC criterion $K = 5$ segmentation.

The determination of the size of the segments and factors that lead to growth delay in the segment is the next thing to be asked after determining the value of $K=3$. In this case, 55.8% or 21 provinces of the sample constitute segment 1, and therefore this segment has the highest number of provinces. The second segment includes 38 provinces, constituting 25.9% of the sample or 10 provinces. In addition to the pooled coefficients from the national model for comparison, Table 8 shows the path coefficients estimated independently within each segment.

Table 7: Path coefficients relevant to each segment for the kept $K = 3$ solution

Path diagram	Original total effects	Segment 1 (n=21)	Segment 2 (n=10)	Segment 3 (n=7)
Antenatal care → Exclusive breastfeeding	0.553	0.808	0.615	-0.275
Antenatal care → Low birth weight	-0.487	-0.610	-0.746	0.328
Antenatal care → Stunting	-0.143	0.071	-0.027	0.018
Early initiation of breastfeeding → Exclusive breastfeeding	-0.242	0.239	-0.400	-1.068
Early initiation of breastfeeding → Stunting	0.210	-0.077	0.389	1.895
Exclusive breastfeeding → Stunting	0.075	0.786	0.190	0.985
Immunization → Stunting	-0.068	-0.604	0.155	0.315
Low birth weight → Stunting	0.540	0.505	1.265	-0.222
Sanitation → Stunting	-0.168	-0.898	0.365	0.019

Segment 1 (21 provinces), there is a highly negative link from sanitation to stunting (-0.898), after which there is a positive link from exclusive breastfeeding to stunting (0.786) and a negative link from immunization to stunting (-0.604). On the surface, this seems to indicate that increased sanitation greatly reduces stunting in this segment, which is consistent with other studies carried out in Indonesia [13], [14]. The problem with the positive figure of exclusive breastfeeding and the negative figure of immunization is that these seem hard to understand as traditional protective measures. This is probably an indication of "reverse targeting".

Segment 2 (10 provinces) most clearly demonstrates a pattern driven by low birth weight. The path from low birth weight to stunting here reaches 1.265, more than double the estimate from the combined model. The effect of antenatal care on low birth weight is also strongest among the three segments (-0.746). This means that limited access to antenatal care in these provinces directly impacts birth weight, which in turn affects stunting. Programs to improve antenatal care in this segment would operate via the same low-birth-weight pathway identified in the combined model [22], [23].

Segment 3 (7 provinces, the smallest group) differs from the other two segments. Both early initiation of breastfeeding (1.895) and exclusive breastfeeding (0.985) show large positive coefficients regarding stunting the opposite of the expected protective effect. Given the small number of provinces, these figures should be viewed as a signal warranting further investigation rather than evidence that breastfeeding has a detrimental impact. Most likely, this segment simply groups together provinces that generally face a severe stunting burden, where breastfeeding indicators and stunting rates move in tandem due to factors outside this model such as food insecurity or exposure to recurrent illness.

Once each province was assigned to the segment for which its posterior membership probability was highest, the resulting groups were plotted on a thematic map of Indonesia, shaded by segment and annotated with each segment's dominant structural pathway, as shown in Fig. 2. Table 8 lists

the province membership underlying that map.

Table 8: Province membership by FIMIX-PLS segment (K = 3)

Segment	Provinces
Segment 1	Sumatera Utara, Riau, Jambi, Sumatera Selatan, Lampung, Kepulauan Riau, Jawa Barat, D I Yogyakarta, Banten, Bali, Nusa Tenggara Timur, Kalimantan Barat, Kalimantan Tengah, Kalimantan Selatan, Kalimantan Utara, Sulawesi Utara, Sulawesi Tengah, Sulawesi Selatan, Gorontalo, Papua Barat Daya, Papua Selatan
Segment 2	Aceh, Sumatera Barat, Bengkulu, DKI Jakarta, Jawa Timur, Kalimantan Timur, Sulawesi Tenggara, Sulawesi Barat, Papua Barat, Papua Tengah
Segment 3	Kep. Bangka Belitung, Jawa Tengah, Nusa Tenggara Barat, Maluku, Maluku Utara, Papua, Papua Pegunungan

Table 8 turns the abstract segment numbers into something a reader can place on a map: Segment 1's 21 provinces run the length of the archipelago, from Sumatera Utara through Kalimantan and into parts of Sulawesi and Papua Barat Daya; Segment 2's 10 provinces include Aceh, DKI Jakarta, and Jawa Timur alongside Kalimantan Timur and Papua Tengah; and Segment 3's 7 provinces cluster around the eastern periphery, Maluku, Maluku Utara, Papua, and Papua Pegunungan, plus Kep. Bangka Belitung, Jawa Tengah, and Nusa Tenggara Barat. The reason that no island or region can be precisely categorized into a particular group is revealing in its own right: geographical closeness does not guarantee that a particular type of stunting pathway will be the dominant factor in the province.

Fig. 2: Thematic map of the three FIMIX-PLS segments

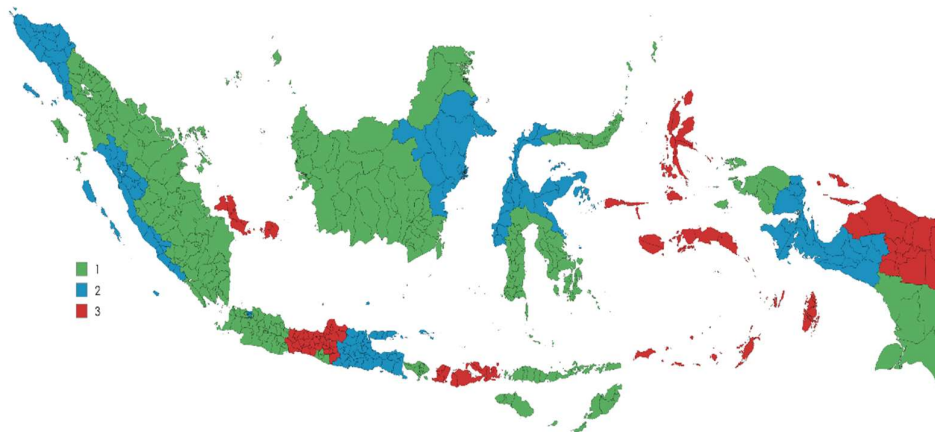


Fig. 2 the map, is exactly what allows this analysis to go beyond statistical tables. When data from the 38 provinces are pooled and averaged, none of the direct influence pathways of the sanitation, birth weight and breastfeeding programmes on stunting cross the 5 percent significance threshold in the pooled model in Table 4 and a national strategy to reduce stunting would regard them as equally weak drivers across all regions. Fig. 2 however, presents a different picture when analyzing the provinces one by one: Provinces in Segment 1 (green) would be most affected by investments in sanitation; Provinces in Segment 2 (blue) would benefit from birth weight programs integrated with prenatal care (antenatal services); Provinces in Segment 3 (red), as stated earlier, require field investigations before the breastfeeding indicators in those areas can be said to have a causal influence, as discussed earlier. This is an example of the practical utility promised in the Introduction, of combining nine structural pathways and three.

4. Conclusion

The research objective was to segment the Indonesian provinces based on the latent variables responsible for stunting, antenatal care, early breastfeeding initiation,

immunization, sanitation, low birth weight, and exclusive breastfeeding through FIMIX-PLS approach, and to create a thematic map from the segmentation obtained. The pooled SEM-PLS model explains 63.0% of the variation in stunting, but only three out of nine theoretical hypotheses can be sustained through bootstrapping: antenatal care increases exclusive breastfeeding and decreases low birth weight, while low birth weight is the only variable that has a direct influence on stunting. The antenatal care influence on stunting can only reach stunting by riding along that birth-weight channel, a fully mediated relationship rather than a direct effect, which is why its own path to stunting looks statistically silent in the pooled model despite being substantively important.

The silence ended up indicating a heterogeneity issue rather than irrelevance. By dividing the 38 provinces into three FIMIX-PLS segments, there was an increase in the explained variance in stunting from 0.63, when pooled, to 0.97 when considering the weighted variance for the three segments. Each segment relied on its own distinct lever that included sanitation for the largest segment, birth weight for the second segment, and breastfeeding for the smallest segment. Mapping those three segments shows the pattern does not simply follow the archipelago's geography, which is precisely why a province-by-province thematic map, rather than a blanket national program or a bare segment table, is the more useful output of an analysis like this one for provincial and district health planners.

Two limitations are worth naming. Segment 3's positive breastfeeding-to-stunting coefficients run counter to the expected protective direction and, given the segment's small size (7 provinces), are read here as a signal for targeted qualitative follow-up rather than a causal finding; and the cross-sectional design cannot rule out reverse targeting, where health programs are intensified precisely in provinces already facing high stunting. Future work could extend the model with household-level socioeconomic and dietary-diversity constructs and test whether these three segments persist against a later year of provincial data.

CRediT Authorship Contribution Statement

Ayu Setya Permatasari: Conceptualization, Methodology, Formal Analysis, Writing – Original Draft, Visualization. **Rahmawati Erma Standsyah:** Conceptualization, Methodology, Validation, Writing – Review & Editing, Supervision, Project Administration.

Declaration of Generative AI and AI-assisted technologies

No generative AI or AI-assisted technologies were used during the preparation of this manuscript.

Declaration of Competing Interest

The authors declare no competing interests.

Ethics Approval and Consent to Participate

Ethics approval was not required for this study, as it relies exclusively on secondary, publicly available, province-level aggregate health statistics.

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Data and Code Availability

The dataset analyzed during the current study is available from the Indonesia Ministry of Health's official health profile publications and can be provided by the corresponding author

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