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SEGMENTING MATERNAL AND CHILD HEALTH DEGREE IN INDONESIA USING SEM-PLS POS

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ABSTRACT

Maternal and child health represents a critical aspect of national development, reflecting both the well-being of the population and the success of regional health equity programs. In Indonesia, disparities in maternal and child health outcomes remain evident across provinces due to socio-economic inequalities and unequal access to health services. This study aims to model the causal relationships between key health determinants and classify provinces based on maternal and child health degree using Structural Equation Modeling with Partial Least Squares (SEM-PLS) combined with Prediction-Oriented Segmentation (POS). The study uses secondary data from 2023 sourced from the Central Statistics Agency (BPS) and the Ministry of Health, covering 34 provinces at the provincial level. Nineteen indicators are grouped into four latent variables: Health Services, Clean and Healthy Living Behavior (PHBS), Environment, and Health Degree. SEM-PLS was applied to identify direct and indirect relationships among these variables, while POS was used to identify homogeneous segments of provinces. The results show that PHBS positively affects Environment (path coefficient = 0.896; $p < 0.001$), while Health Services negatively affect Health Degree (path coefficient = –0.668; $p < 0.01$), indicating the presence of indirect pathways influencing health outcomes. The segmentation analysis identified three segments: Segment 1 includes provinces with moderate outcomes but weak child health services; Segment 2 includes provinces with relatively better maternal outcomes but sanitation gaps; Segment 3 consists of provinces with the most critical health conditions, including high stunting and malnutrition rates. These findings demonstrate that PHBS is a dominant influencing factor, while improved service access alone does not always translate to better outcomes. The SEM-POS approach effectively identifies segment-specific health disparities, supporting more targeted policy interventions to improve maternal and child health in Indonesia.

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1. INTRODUCTION

Health is a key foundation of human development, playing a crucial role in determining the quality of life, social well-being, and economic productivity of a nation [1]. In Indonesia, efforts to improve public health have become the main focus of various national development programs, particularly in the area of maternal and child health (MCH), which serves as a core component of population well-being and national development targets, including the Sustainable Development Goals (SDGs) [2]. However, achieving equitable maternal and child health outcomes across Indonesia still faces major challenges, given the large population, socio-economic diversity, and geographic disparities in access to health services

The health degree of the Indonesian population is commonly assessed using various indicators, including maternal and child health services coverage, nutritional outcomes, and preventive health behaviors. Despite improvements in national health programs, significant interregional disparities persist, especially in maternal and child health outcomes [3]. Reports from the Ministry of Health indicate that provinces in remote areas, particularly in Eastern Indonesia, continue to experience low access to quality maternal and child health services compared to the more developed western regions such as Java and Sumatra [4].

Socio-economic inequalities, including education, employment, and income disparities, further exacerbate maternal and child health gaps. Vulnerable populations with low socio-economic status often experience inadequate health knowledge, poor access to services, and higher risks of malnutrition, stunting, and child morbidity [5]. Although programs such as the National Health Insurance (JKN) have been implemented to improve access [6], evaluating their effectiveness in reducing maternal and child health disparities requires comprehensive and segment-specific analysis.

To address these complexities, this study applies a multidimensional analytical approach, using SEM with the Partial Least Squares (PLS) approach combined with POS segmentation. SEM-PLS is particularly suitable for health research involving complex latent constructs, non-normal data distribution, and relatively small samples (34 provinces). It allows simultaneous modeling of measurement and structural relationships, making it effective in analyzing interactions between health services, behavioral factors, environmental conditions, and health outcomes [7]. POS segmentation further enhances the analysis by capturing unobserved heterogeneity among provinces, classifying them into homogeneous segments based on similar determinant patterns, which enables more targeted and effective policy recommendations [8].

The SEM-PLS POS segmentation approach has previously been applied by Eliani et al. [9] to classify provinces in Indonesia based on maternal and child health indicators. While their study offered valuable initial insights, it remained limited in scope by not incorporating mediating variables to explore indirect causal relationships and by not presenting the segmentation outcomes in a spatial format that could inform regional policy planning. This current study builds upon and advances that approach by introducing environmental factors as mediating variables within the structural model and by spatially visualizing the segmentation results using province-level maps. These enhancements allow for a deeper understanding of interregional disparities, more accurate identification of segment characteristics, and more actionable and targeted policy recommendations to improve maternal and child health outcomes in Indonesia.

2. RESEARCH METHODS

2.1 Structural Equation Modeling Analysis (SEM)

SEM is a multivariate statistical method that is widely used to address basic problems in decision-making in the scope of social and behavioral sciences, and has also been developed in other disciplines through measurements that involve variables that cannot be directly measured, so it requires indicator variables as measurable variables [8]. SEM can be used to test the structural equation model, which explores the relationship between endogenous and exogenous latent variables. Furthermore, it helps test the measurement model, which examines the relationship between indicator variables and the latent variables they represent [9].

2.2 Partial Least Squares (PLS)

Partial Least Squares (PLS) is a method for solving SEM, often referred to as soft modeling because it bypasses the assumptions required by OLS (Ordinary Least Squares) regression, such as the need for multivariate normality and the absence of multicollinearity among exogenous variables. While PLS is used to examine the existence or absence of relationships between latent variables, it can also be employed to validate theories [10].

In SEM-PLS, the model has two main aspects: the outer and inner models. The outer model describes the relationship between latent variables and their indicators. Outer models can be either reflective or formative. A reflective model considers latent variables to be reflections of the indicators. This model's causal relationship flows from the latent variable to the indicator. Below is the equation for the indicator model of the exogenous variable [13].

$$x_{(q\times 1)} = \mathbf{\Lambda}_{x(q\times m)}\xi_{(m\times 1)} + \delta_{(q\times 1)}, \tag{1}$$

Meanwhile, the equation of the indicator model for endogenous variables, namely:

$$y_{(p\times 1)} = \mathbf{\Lambda}_{y(p\times n)}\eta_{(n\times 1)} + \varepsilon_{(p\times 1)}. \tag{2}$$

with,

x : exogenous latent variable indicators,
y : endogenous latent variable indicators,
Λ_x : matrix loading indicator relationship with exogenous variables,
Λ_y : matrix loading indicator relationship with endogenous variables,
ξ : exogenous latent variable,
δ : measurement errors in exogenous variable indicators,
ε : measurement errors in endogenous variable indicators,
η : endogenous latent variable,
q : numerous indicators of exogenous variables,
p : numerous indicators of endogenous variables,
m : the number of exogenous variables,
n : the number of endogenous variables.

The above Eqs. (1) and (2) represent the outer model, where the observed indicators reflect their corresponding latent constructs. For example, the indicator 'percentage of toddlers weighed' reflects the latent construct of health services.

The outer model evaluation step is carried out to see the validity and reliability of the model. The latent variable is reflective, so convergent validity and discriminant validity are used for the evaluation [14]. Convergent validity measures the correlation between latent variables and indicators in reflective measurement models. The rule of thumb used to evaluate is outer loading value > 0.6. Discriminant validity deals with the principle that measures of different latent variables should not be highly correlated [13]. Cross-loading, Fornell-Larcker Criterion, and AVE values are indicators for measuring discriminant validity. Cross-loading evaluates whether each indicator is more correlated with the latent variable than with other latent variables; the indicator's cross-loading value on the measured latent variable must be higher than the cross-loading value of the indicator on the other latent variable.

The Fornell-Larcker Criterion compares the square root of the Average Variance Extracted (AVE) for each latent variable with the correlation values between latent variables in the model. The value of the latent variable must be higher than the correlation value with other latent variables. Then, the AVE value measures the proportion of indicator variance that latent variables can explain; with an AVE value> 0.5, the correlation between latent variables shows good discriminant validity [15]. The reliability test proves the instrument's accuracy, consistency, and correctness in measuring latent variables. The rule of thumb usually used to assess the reliability of latent variables is the composite reliability value > 0.7 [16].

The inner model describes the relationship between exogenous and endogenous latent variables. This test was done with the help of a bootstrap. The following is an equation from the inner model [13].

$$\eta_{(nx1)} = \mathrm{B}_{(nxn)}\eta_{(nx1)} + \Gamma_{(nxm)}\xi_{(mx1)} + \boldsymbol{\zeta}_{(nx1)}, \tag{3}$$

with

η : endogenous latent variable,
B : endogenous latent variable path coefficients,
Γ : pathway coefficients between exogenous latent variables and endogenous latent variables,
ξ : exogenous latent variable,
$\boldsymbol{\zeta}$: structural measurement error vector,
m : the number of exogenous variables,
n : the number of endogenous variables.

The above Eq. (3) captures the structural relationships, illustrating how determinants like PHBS and health services directly or indirectly influence environmental factors and the overall health degree.

Statistical measures used to evaluate the inner model, named path coefficient, are used to identify the significance of the relationship between latent variables. Path coefficient estimates two different effects, which are the direct effect and the indirect effect. In direct effects, the relationship between latent variables is achieved without a mediator; meanwhile, in indirect effects, the relationship between latent variables is achieved through a mediator that connects two latent variables. Coefficient of Determination (R^2) shows the level of goodness on a structural model, which is used to identify the extent to which the effect of exogenous latent variables on endogenous variables. The R^2 value has a range of 0 to 1 if the R^2 value is closer to 1, which means the model used is very good at explaining variations. Criteria for the boundaries of the R^2 value is divided into three classifications: if the $\mathrm{R}^2 > 0.67$ is obtained, the model is included in the strong category. If a value of $0.33 \leq \mathrm{R}^2 < 0.67$ is obtained, the model can be said to be in the moderate category if a value of $0.19 \leq \mathrm{R}^2 < 0.33$ is obtained, the model is in the weak category, and for a value of $\mathrm{R}^2 < 0.19$, the model is in the very weak category [14].

2.3 Prediction-Oriented Segmentation (POS)

According to Sarstedt and friends [8] many cases have unobserved heterogeneity that can disguise different relationships between latent concepts in a cause-effect model. Recent research has applied latent class techniques to evaluate PLS path models. Accordingly, applying some latent response-based segmentation that identifies unobserved heterogeneity is important. PLS-POS is one of the segmentation methods oriented to predict the relationship between latent variables and was specifically created to complement path modeling in PLS. This method follows a clustering method that places observations deterministically in groups and uses distance measures to replace the observations into more appropriate groups to increase the R^2 value, which is the predictive power of the endogenous latent variables model.

One of the advantages of PLS-POS is that it employs a strictly nonparametric approach, which does not rely on any distribution assumptions. This characteristic allows it to uncover heterogeneity within the outer and inner models. It can also be applied to all path models without concern for the type of measurement model, data distribution, sample size, relative segment size, multicollinearity, or structural model complexity [8]. The PLS-POS method can identify heterogeneity in the reflective model when heterogeneity is present in the structural model. This means that if the reflective measurement model exhibits heterogeneity, it can be the underlying cause of the heterogeneity observed in the structural model.

PLS-POS emphasizes enhancing the predictive accuracy for each group by minimizing the total sum of squared residuals associated with the endogenous latent variables within the PLS model path. As a result, the objective criterion is represented by the sum of the R^2 values of each group that are specified and calculated in detail. Each observation placement in PLS-POS ensures an increase in the objective criterion because it is based on a hill-climbing approach. This objective criterion is suitable for application to all PLS path models, whether the model contains reflective or formative measures. The total distance measure used in PLS-POS, which is [9]:

$$D_{kig} = \sum_{b=1}^{B} \sqrt{\frac{e_{big}^2}{\sum_{i=1}^{I_k} e_{big}^2}}, \tag{4}$$

with:

e_{big}^2 : residuals from observation i in the alternative group g $(k \neq g; k, g \in G)$,
$\sum_{i=1}^{I_k} e_{big}^2$: sum residuals in the baseline group k,
b : endogenous latent variable,

I_k : sample size in the baseline group k.

2.4 Dataset

This research is included in the quantitative descriptive research category, which describes an event based on the characteristics and facts found. The data used is secondary data from 2023 obtained from publications by the Central Statistics Agency (BPS) [4], and the Ministry of Health of the Republic of Indonesia [17]. The selection of 2023 data is based on the most recent and complete national health statistics available, providing the latest representation of health conditions across Indonesian provinces. This study uses provincial-level data, with a total of 34 observations corresponding to the 34 administrative provinces of Indonesia.

The operationalization of each latent variable in this study is based on health indicators derived from national health statistics published by BPS and the Ministry of Health. In total, four latent variables with nineteen indicators were utilized to comprehensively capture key health determinants and outcomes. Table 1 provides the detailed list of latent variables along with their respective indicators used in the modeling process.

Table 1. Indicator of Each Latent Variable

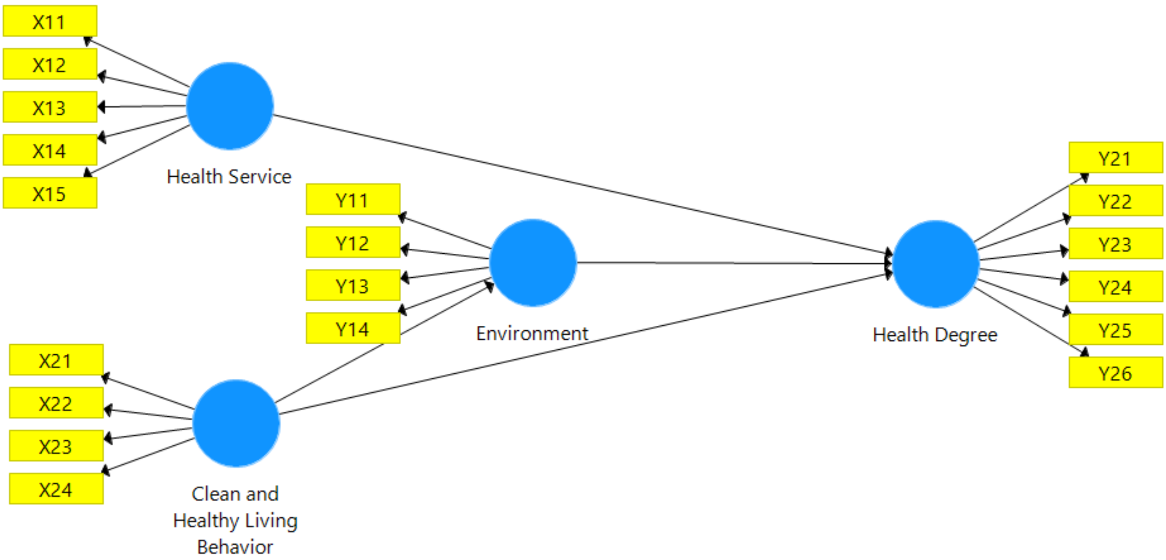
Latent Variable		Indicator
Health Service (ξ_1)	X_{11}	Percentage of Pregnant Women Who Received Blood Supplement Tablets
	X_{12}	Percentage of Births at Health Facilities
	X_{13}	Percentage of Newborns That Received Early Initiation Of Breastfeeding
	X_{14}	Percentage of 6 - 11 Months Babies Received Vitamin A
	X_{15}	Percentage of Weighed Toddlers
Clean and Healthy Living Behavior (ξ_2)	X_{21}	Percentage of Village Stops Open Defecation
	X_{22}	Percentage of Women ≥ 15 Years Old Smoked during the Last Month
	X_{23}	Percentage of 0 - 6 Months Babies Received Exclusive Breastfeeding
	X_{24}	Percentage of Babies Received Complete Basic Immunization
Environment (η_1)	Y_{11}	Population Density per km^2
	Y_{12}	Percentage of Poor Population
	Y_{13}	Percentage of Villages Adopting Community-Based Total Sanitation
	Y_{14}	Percentage of Health Facilities Implementing Medical Waste Management
Health Degree (η_2)	Y_{21}	Maternal Mortality Rate (MMR)
	Y_{22}	Infant Mortality Rate (IMR)
	Y_{23}	Percentage of Pregnant Women Reactive to Hepatitis B surface Antigen (HBsAg)
	Y_{24}	Percentage of Toddlers with Pneumonia
	Y_{25}	Percentage of Malnourished Toddlers
	Y_{26}	Percentage of Stunting

Each indicator was selected by considering its relevance to national health priorities and alignment with internationally recognized health measurement frameworks, particularly the Sustainable Development Goals (SDGs)[18]. This approach ensures the indicators not only reflect Indonesia's public health targets but also maintain comparability with global health development standards. The Health Service indicators emphasize key maternal and child health services, aligned with national programs such as the National Health Insurance (JKN) and Stunting Reduction Acceleration Program [17]. For instance, the "percentage of births at health facilities" serves as a proxy for safe childbirth coverage, closely associated with maternal and infant mortality reduction. The Clean and Healthy Living Behavior (PHBS) indicators capture preventive health behaviors, such as the "percentage of babies receiving complete basic immunization" and "village stops open defecation," both reflecting sanitation and disease prevention efforts [17]. The Environment indicators represent physical and socio-environmental factors influencing health, with "population density" illustrating the risks of disease transmission and service access disparities [4]. Lastly, Health Degree indicators focus on ultimate health outcomes, including stunting, malnutrition, infant mortality rate (IMR), and maternal mortality rate (MMR), all of which are core SDG targets under Goal 3: Good Health and Well-being) [18].

This study specifically excludes general demographic indicators, such as life expectancy or overall disease prevalence, to maintain analytical focus on maternal and child health outcomes. This selection aligns with SDG 3 targets and national health priorities emphasizing improvements in maternal and child health indicators.

2.5 Conceptual Framework

This study's structural model of health degree comprises four latent variables and nineteen indicators, as summarized in Table 1. The two exogenous latent variables are Health Services (ξ_1) and Clean and Healthy Living Behavior (ξ_2), while the two endogenous latent variables are Environment (η_1) and Health Degree (η_2). The Environment variable functions as a mediator, transmitting the indirect effect of Clean and Healthy Living Behavior on Health Degree. Both Health Services and Clean and Healthy Living Behavior are hypothesized to have direct positive effects on Health Degree, while Clean and Healthy Living Behavior also exerts an indirect positive effect through the Environment. The complete structural relationships among the latent variables and their respective indicators are illustrated in Fig. 1.



(Source: SmartPLS)

Figure 1. Health Degree Path Diagram

In this context, a hypothesis is defined as a theoretical proposition that specifies the expected causal relationship between variables based on previous literature and conceptual models. The formulation of hypotheses in this study is grounded in prior research and established theoretical frameworks, including Andersen's Behavioral Model of Health Services [19], the Health Ecology Model [20], and behavioral-environmental interaction models [21].

Based on the conceptual framework, this study formulates the following hypotheses:

H_1 : Clean and Healthy Living Behavior has a positive and significant indirect effect on Health Degree through Environment [19],

H_2 : Health Services have a positive and significant direct effect on Health Degree [20],

H_3 : Clean and Healthy Living Behavior has a positive and significant direct effect on Environment [22],

H_4 : Environment has a positive and significant direct effect on Health Degree [21].

Based on these hypotheses, the subsequent analysis was conducted using Structural Equation Modeling with Partial Least Squares (SEM-PLS) combined with Prediction-Oriented Segmentation (POS) to empirically test the proposed relationships and classify provinces into homogeneous health segments. The analytical procedure consisted of three stages: evaluating the measurement model (outer model), testing the structural model (inner model), and applying POS segmentation, ensuring both measurement reliability and segment-specific classification were systematically addressed.

3. RESULTS AND DISCUSSION

The following section presents the empirical findings of the SEM-PLS and POS analysis, starting with the evaluation of the measurement model to ensure the validity and reliability of the indicators used in the study.

3.1 Measurement Model Evaluation (Outer Model)

Evaluation of the measurement model (outer model) includes an assessment of each indicator's validity and reliability against its latent variable. The validity carried out is convergent validity and discriminant validity. The convergent validity test in SEM-PLS can be seen through the outer loadings value. Indicators can be labeled valid with an outer loading value > 0.6.

Table 2. First Step Convergent Validity Testing Results

Latent Variable	Indicator	Outer Loadings	Information
Health Degree (Y_2)	Y_{21}	- 0.572	**Invalid**
	Y_{22}	- 0.583	**Invalid**
	Y_{23}	0.846	Valid
	Y_{24}	- 0.147	**Invalid**
	Y_{25}	0.788	Valid
	Y_{26}	0.804	Valid
Environment (Y_1)	Y_{11}	0.374	**Invalid**
	Y_{12}	- 0.479	**Invalid**
	Y_{13}	0.880	Valid
	Y_{14}	0.896	Valid
Health Service (X_1)	X_{11}	0.839	Valid
	X_{12}	0.873	Valid
	X_{13}	0.144	**Invalid**
	X_{14}	0.956	Valid
	X_{15}	0.878	Valid
Clean and Healthy Living Behavior (X_2)	X_{21}	0.916	Valid
	X_{22}	0.102	**Invalid**
	X_{23}	0.874	Valid
	X_{24}	0.847	Valid

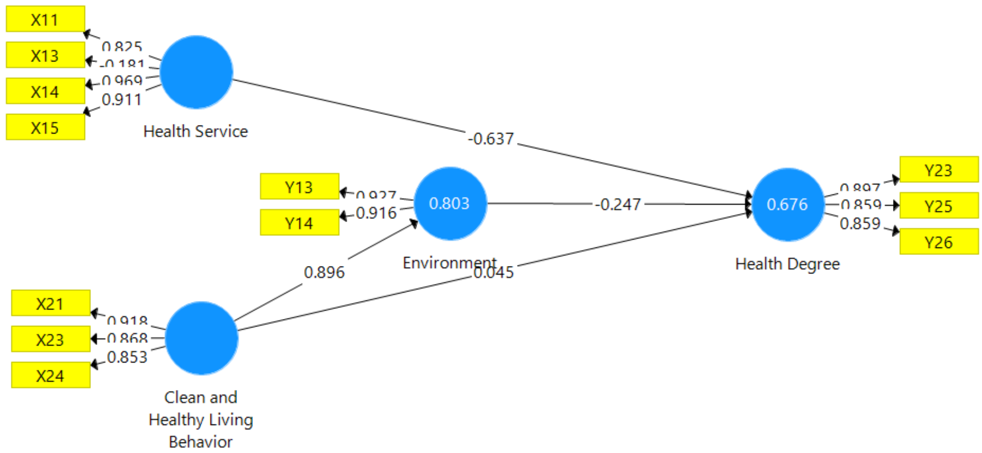
The above Table 2 shows the outer loading values of all indicators associated with each latent variable. Several indicators have outer loading values below 0.7, which is the ideal threshold. However, following the Hair et al. [7], indicators with loadings between 0.5 and 0.7 may still be retained if the construct's AVE and Composite Reliability (CR) meet the minimum requirements. Indicators with outer loadings below 0.6 were removed from the model to enhance parsimony and ensure strong convergent validity.

In addition, some indicators showed negative outer loading values. These indicators were carefully examined to assess whether reverse scoring was appropriate. After reviewing the original item definitions and directional alignment, no reverse-coded items were conceptually identified. Therefore, the negative-loading indicators were excluded from the analysis to maintain consistency and measurement validity. The model was then re-estimated using only indicators that met the convergent validity criteria.

Table 3. Second Step Convergent Validity Testing Results

Latent Variables	Indicator	Outer Loadings	Information
Environment (Y_1)	Y_{13}	0.927	Valid
	Y_{14}	0.916	Valid
Health Degree (Y_2)	Y_{23}	0.896	Valid
	Y_{25}	0.859	Valid
	Y_{26}	0.860	Valid
Health Service (X_1)	X_{11}	0.843	Valid
	X_{13}	0.874	Valid
	X_{14}	0.954	Valid
	X_{15}	0.878	Valid
Clean and Healthy Living Behavior (X_2)	X_{21}	0.918	Valid
	X_{23}	0.868	Valid
	X_{24}	0.853	Valid

The above Table 3 shows that the outer loading values of all indicators within each latent variable exceed 0.6, indicating that all indicators meet the required validity threshold and are eligible for further analysis. The structural path diagram after eliminating invalid indicators is presented in Figure 2.



(Source: SmartPLS)

Figure 2. Path Diagram After Elimination

Based on the path diagram (Fig. 2), Clean and Healthy Living Behavior (PHBS) shows a strong positive effect on the Environment (path coefficient = 0.896), indicating that improved community behavior, such as reducing open defecation, promoting exclusive breastfeeding, and ensuring complete childhood immunizations, significantly contribute to better environmental health outcomes. This result indicates that Environment does not significantly mediate the relationship between PHBS and Health Degree (path coefficient = 0.045), thus challenging the initial hypothesis. Although PHBS improves environmental conditions, these improvements may not yet translate into measurable health outcomes due to lag effects or indirect mechanisms. This finding is consistent with Mariana et al [23], who reported that improvements in household sanitation and maternal behavior significantly reduced child morbidity, underscoring the indirect impact of behavioral changes through environmental improvements.

In contrast, Health Service shows a negative direct effect on Health Degree (path coefficient = -0.637), which may reflect the phenomenon where regions with poorer health outcomes receive more intensive health service interventions, yet without immediate improvements in overall health indicators. Similar findings were reported in the JKN review by TNP2K [24], which highlighted that the expansion of health service access through JKN did not consistently lead to better health outcomes, particularly in disadvantaged areas, due to systemic inequalities in service quality and supporting infrastructure.

These findings suggest the need for integrated health policy strategies that address not only service coverage and individual behavior but also environmental and systemic factors, particularly in underserved provinces.

Discriminant validity evaluation in this study was conducted using cross-loading analysis, the Fornell-Larcker criterion, and Average Variance Extracted (AVE). Table 4 presents the cross-loading values, showing how strongly each indicator correlates with its corresponding latent variable compared to other latent variables.

Table 4. Cross-Loading Value

Indicator	Health Degree	Environment	PHBS	Health Service
Y_{13}	- 0.723	**0.927**	0.855	0.908
Y_{14}	- 0.687	**0.916**	0.794	0.737
Y_{23}	**0.896**	- 0.662	- 0.542	- 0.688
Y_{25}	**0.859**	- 0.688	- 0.709	- 0.752
Y_{26}	**0.860**	- 0.650	- 0.633	- 0.691
X_{11}	- 0.714	0.785	0.714	**0.843**
X_{13}	- 0.693	0.785	0.715	**0.874**
X_{14}	- 0.777	0.852	0.867	**0.954**
X_{15}	- 0.714	0.756	0.770	**0.878**
X_{21}	- 0.662	0.778	**0.918**	0.710

Indicator	Health Degree	Environment	PHBS	Health Service
X_{23}	- 0.673	0.805	**0.868**	0.821
X_{24}	- 0.570	0.783	**0.853**	0.753

The above Table 4 shows that each indicator's loading value is highest on its respective latent variable compared to other constructs, indicating satisfactory discriminant validity. This condition satisfies the first requirement for discriminant validity. The Fornell-Larcker Criterion and AVE values were subsequently analyzed to further confirm the discriminant validity.

Table 5. Fornell-Larcker Criterion Value

Latent Variable	Health Degree	Environment	PHBS	Health Service
Health Degree	**0.872**			
Environment	0.766	**0.921**		
PHBS	0.723	0.896	**0.880**	
Health Service	0.816	0.896	0.866	**0.888**

In Table 5, the diagonal values represent the square root of the Average Variance Extracted (AVE), while the off-diagonal values indicate the correlation coefficients. Discriminant validity is confirmed if the square root of each AVE is greater than the correlation coefficients in the corresponding rows and columns [25]. The square root of AVE values of the health degree and environment latent variables are 0.872 and 0.921, respectively, greater than the correlation values with the other latent variables. There are a few disputes regarding the Environment-PHBS and Health Service-Environment construct. However, the differences are negligible, with values of 0.016 and 0.008, respectively, and can be ignored [25]. This measurement model's discriminant validity is supported, confirming that the constructs are distinctly valid. Therefore, further evaluation is necessary by looking at the AVE value in Table 6.

Table 6. Average Variance Extracted (AVE) Value

Latent Variable	Average Variance Extracted (AVE)
Health Degree	0.760
Environment	0.849
PHBS	0.774
Health Service	0.789

The above Table 6 shows that all latent variables have satisfactory convergent validity, with AVE values exceeding the 0.5 threshold. Specifically, the AVE values for Health Degree, Environment, PHBS, and Health Services are 0.760, 0.849, 0.774, and 0.789, respectively. These results confirm that each construct explains a substantial portion of the variance in its indicators and can be used for further analysis.

Table 7. Composite Reliability Value

Latent Variable	Composite Reliability
Health Service	0.937
PHBS	0.911
Environment	0.918
Health Degree	0.905

The above Table 7 shows that the composite reliability values of all latent variables exceed 0.7, indicating good internal consistency reliability. Based on Fig. 2, the measurement equation model for each exogenous and endogenous latent variable is presented below.

1. Health Service Variable Measurement Model (ξ_1)

$$X_{11} = 0.874\xi_1 + \delta_1, \tag{5}$$
$$X_{13} = 0.954\xi_1 + \delta_2, \tag{6}$$
$$X_{14} = 0.878\xi_1 + \delta_3, \tag{7}$$
$$X_{15} = 0.843\xi_1 + \delta_4. \tag{8}$$

2. Clean and Healthy Living Behavior Variable Measurement Model (PHBS) (ξ_2)

$$X_{21} = 0.918\xi_2 + \delta_5, \tag{9}$$

$$X_{23} = 0.868\xi_2 + \delta_6, \tag{10}$$
$$X_{24} = 0.853\xi_2 + \delta_7. \tag{11}$$

3. Environment Variable Measurement Model (η_1)

$$Y_{13} = 0.927\eta_1 + \varepsilon_1, \tag{12}$$
$$Y_{14} = 0.916\eta_1 + \varepsilon_2. \tag{13}$$

4. Health Degree Variable Measurement Model (η_2)

$$Y_{23} = 0.896\eta_2 + \varepsilon_3, \tag{14}$$
$$Y_{25} = 0.859\eta_2 + \varepsilon_4, \tag{15}$$
$$Y_{26} = 0.860\eta_2 + \varepsilon_5. \tag{16}$$

3.2 Structural Model Evaluation (Inner Model)

The evaluation of the structural model (inner model) encompasses the path coefficient and the coefficient of determination. The path coefficient comprises two types of effects: indirect and direct effects. Direct effect testing assesses the strength of the relationship between endogenous and exogenous latent variables by examining the p-value and the path coefficient value. A p-value of ≤ 0.05 indicates a strong correlation between the latent variables.

Table 8. Direct Effect

Latent Variable	Original Sample	p-value
Environment → Health Degree	- 0.191	0.450
PHBS → Health Degree	0.026	0.916
PHBS → the Environment	0.896	0.000
Health Service → Health Degree	- 0.668	0.002

The above Table 8 shows that the latent variable Environment does not have a significant direct effect on Health Degree (p-value = $0.450 \geq 0.05$). Similarly, PHBS (Clean and Healthy Living Behavior) also does not exhibit a significant direct effect on Health Degree (p-value = $0.916 \geq 0.05$). However, PHBS has a strong positive effect on Environment (path coefficient = 0.896; p-value = $0.000 \leq 0.05$), indicating a significant relationship between behavioral factors and environmental health outcomes. Meanwhile, Health Service shows a significant negative direct effect on Health Degree (path coefficient = –0.668; p-value ≤ 0.05), This result should not be misunderstood as meaning that health services make health worse. Instead, it likely shows a reverse pattern: provinces with serious health problems, like high rates of stunting, malnutrition, and infant deaths, usually receive more health services because they are in greater need.

The negative relationship may also happen because the indicators used to measure Health Degree, such as mortality and malnutrition, do not quickly improve, even when access to health services increases. These are long-term outcomes that take time to change. A higher use of health services often reflects an urgent response to poor health conditions, not that the services are failing. A similar explanation appears in the TNP2K report [24], which found that expanding health services through the JKN program in high-need areas didn't always lead to quick improvements because of deeper problems, like weak infrastructure, low service quality, and unequal access to healthcare.

Table 9. Indirect Effect

Latent Variable	Original Sample	T-Statistics	p-value
PHBS → Environment, → Health Degree	-0.171	0.751	0.453

The indirect effect test assesses the significance of exogenous latent variables in influencing endogenous latent variables through mediating factors. Table 9 shows that the indirect effect of PHBS (Clean and Healthy Living Behavior) on Health Degree through Environment is statistically insignificant, with a p-value ≥ 0.05 and a t-statistic < 1.96. These results indicate that the original hypothesis (H1) proposing an indirect effect of PHBS on Health Degree through Environment is not supported by the data ($p = 0.453 \geq 0.05$). Therefore, the mediating role of Environment is rejected in this model. This may suggest that while PHBS can improve environmental conditions, such improvements do not yet directly translate into measurable changes in maternal and child health outcomes.

Table 10. R-Square Value

Endogenous Latent Variable	R^2
Health Degree	0.676
Environment	0.803

The above Table 10 shows that the model explains 67.6% of the variance in Health Degree (R^2 = 0.676), while the remaining 32.4% is influenced by other factors not included in the model. For environment, the model explains 80.3% of its variance (R^2 = 0.803), indicating good explanatory power for environmental outcomes.

The following structural equations summarize the relationships between latent variables in the final model.

1. Environment Latent Variable Structural Model (η_1)

$$\eta_1 = 0.896\xi_1 + \zeta_1 \tag{17}$$

2. Health Degree Latent Variable Structural Model (η_2)

$$\eta_2 = -0.191\eta_1 - 0.668\xi_1 + 0.026\xi_2 + \zeta_2 \tag{18}$$

The final structural model reflects the cumulative effects of exogenous determinants on health outcomes, particularly emphasizing the indirect pathways through environmental mediation.

3.3 Segment Determination with PLS-POS

Average Weighted R^2 is an R^2 value adjusted to the number of segments. Determining the number of segments is obtained from the test results obtained during the estimation process in SmartPLS, the model with $k = 4$ failed or could not produce a valid model. For this reason, to maintain the validity of the model, only $k = 2$ and $k = 3$ will be used to compare and determine the best number of segments.

Table 11. Weight Comparison of $\mathbf{R^2}$ **with** $\mathbf{k = 2}$ **and** $\mathbf{k = 3}$

k	Average Weighted R-Squares	
	Health Degree	Environment
2	0.840	0.831
3	0.939	0.838

The above Table 11 shows that the Average Weighted R^2 value is higher when the number of segments is set to k = 3 compared to k = 2, indicating a better explanatory power of the model with three segments. Therefore, the provincial classification based on health degree was finalized into three segments. The segmentation results suggest that members within each segment share homogeneous characteristics in terms of health determinants and outcomes. Detailed provincial groupings for each segment are presented in Table 12. This classification allows for more targeted health policy recommendations based on segment-specific characteristics.

Table 12. Provincial Grouping by Segment

Segment	Province Name
1	Bengkulu, Gorontalo, Banten, DI Yogyakarta, West Kalimantan, Riau Islands, Lampung, South Papua, and Highland Papua.
2	DKI Jakarta, Aceh, Bali, Jambi, West Java, Central Java, North Kalimantan, Maluku, West Nusa Tenggara, Papua, North Maluku, West Papua, Central Papua, West Sumatra, North Sumatra, West Sulawesi, South Sumatra, South Sulawesi, Central Sulawesi, Southeast Sulawesi.
3	East Java, Bangka Belitung Islands, South Kalimantan, East Kalimantan, Central Kalimantan, Riau, East Nusa Tenggara, Southwest Papua.

The above Table 13 summarizes the average values of selected health indicators across segments, providing an overview of key differences in service utilization and health behaviors among provincial groups.

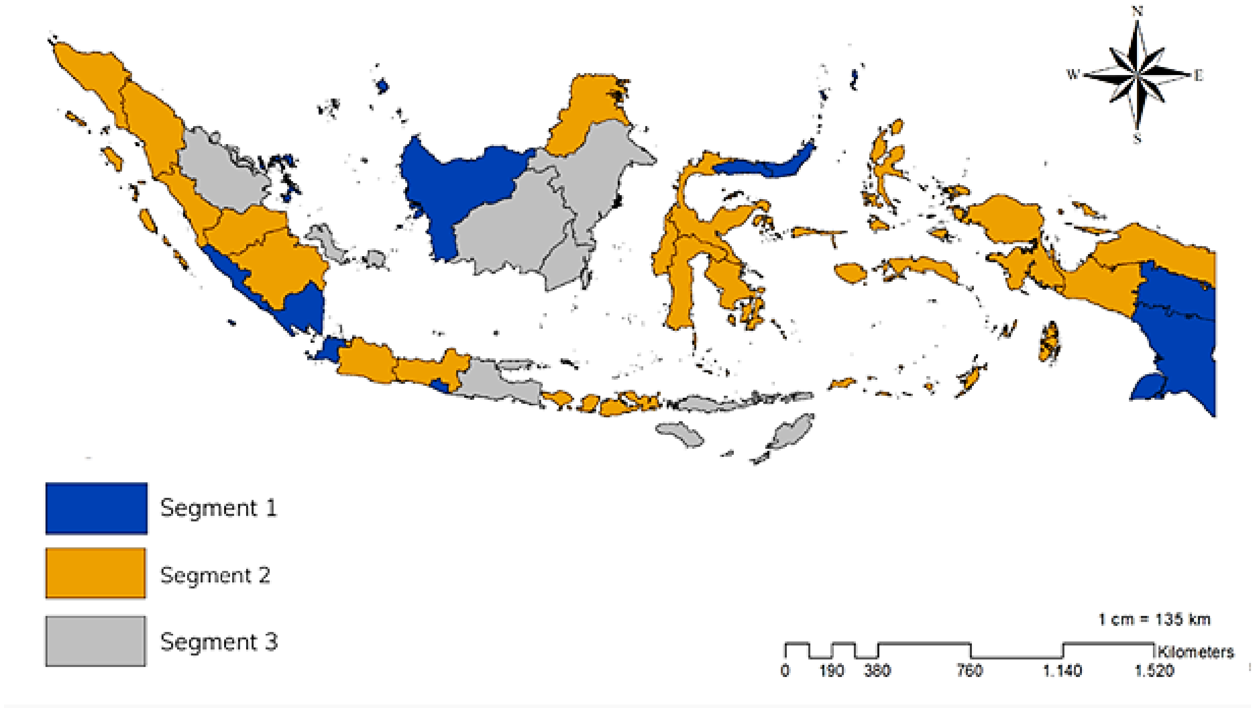
Table 13. **Average Characteristics of Segments**

	Indicator	Segment		
		1	**2**	**3**
X_{11}	Pregnant Women Who Received Blood Supplement Tablets (%)	84.71	**78.74**	82.05
X_{13}	Newborn Babies Who Received Early Initiation of Breastfeeding (%)	87.21	85.83	**83.20**
X_{14}	Babies Aged 6 - 11 Months Who Receive Vitamin A (%)	**81.96**	83.64	84.18
X_{15}	Toddlers Who Are Weighed (%)	66.17	69.62	**63.96**
X_{21}	Village Stops Open Defecation (%)	**54.03**	64.10	67.01
X_{23}	Babies Aged 0-6 Months Who Get Exclusive Breast Milk	**52.77**	53.09	54.19
X_{24}	Babies Who Received Complete Basic Immunization	**78.39**	82.69	81.34
Y_{13}	Villages Adopting Community-Based Total Sanitation (%)	**80.41**	82.91	87.36
Y_{14}	Health Facilities Practicing Medical Waste Management (%)	44.69	**37.45**	41.14
Y_{23}	Pregnant Women Testing Positive for Hepatitis B Surface Antigen (HBsAg) (%)	1.79	2.05	**2.21**
Y_{25}	Malnourished Toddlers (%)	0.74	0.59	**0.80**
Y_{26}	Stunted Toddlers (%)	23.47	23.73	**23.98**

The provinces included in Segment 1 require targeted improvements in several key indicators, particularly the percentage of babies aged 6–11 months who receive vitamin A, babies aged 0–6 months who are exclusively breastfed, and babies who receive complete basic immunization. Several factors contribute to the low performance of these indicators, including insufficient maternal knowledge [26], long distance to health facilities [27], and shortages of healthcare workers in remote areas [28]. Moreover, the low percentage of villages practicing open defecation cessation and implementing community-based total sanitation programs reflects persistent issues in sanitation awareness and infrastructure in rural areas [22].

In segment 2, a notable concern is the low percentage of pregnant women receiving iron supplementation (blood supplement tablets). Despite the availability of health services, this gap is primarily attributed to limited maternal knowledge regarding the importance of iron supplementation [29]. Another area of concern in Segment 2 is the low percentage of health facilities implementing medical waste management practices, especially in regions outside Java Island. This issue is linked to inadequate infrastructure and limited budget allocations [30], , while in Java Island provinces, the issue stems from weak government monitoring and evaluation of medical waste management practices [31].

In segment 3, several health indicators demand attention, including the low coverage of early initiation of breastfeeding among newborns, the low percentage of toddlers weighed, and the higher prevalence of malnutrition and stunting among children. These outcomes are closely associated with insufficient maternal knowledge about child nutrition [32]. Additionally, the low coverage of hepatitis B surface antigen (HBsAg) testing among pregnant women is driven by limited access to HBsAg screening at health facilities and low awareness among expectant mothers regarding its importance [33].



(Source: ArcGIS)

Figure 3. Segmentation Map of Indonesia's Health Degree in 2023

The above Fig. 3 illustrates the spatial distribution of Indonesia's health degree segmentation in 2023. Provinces are grouped into three segments based on the similarity of their health indicators, with Segment 1 (blue) representing provinces with lower health degree scores, Segment 2 (orange) reflecting moderate scores, and Segment 3 (gray) encompassing provinces with relatively higher health degree outcomes. This segmentation map highlights significant geographical disparities in public health conditions, where eastern regions tend to be overrepresented in Segment 1, while Segment 3 is predominantly concentrated in more developed western provinces.

4. CONCLUSION

This study concludes that the application of the SEM-POS approach is effective in identifying variations in health determinants and segmenting Indonesian provinces based on their health profiles. The findings revealed three distinct health segments that require differentiated policy responses. Provinces in Segment 1, characterized by moderate health conditions but weaknesses in maternal and child health indicators, should prioritize improvements in healthcare service quality, including expanding immunization and maternal care coverage. Segment 2 provinces show relatively better health conditions but face challenges in environmental factors, particularly sanitation and medical waste management, thus requiring policies that focus on improving sanitation infrastructure and promoting healthy living behavior. Meanwhile, Segment 3 provinces experience the most pressing health issues, especially in child malnutrition and stunting, necessitating targeted interventions such as community-based nutrition programs and improved access to early-life health services. This segmentation-based approach provides a more precise direction for health policy, enabling provincial governments to allocate resources more effectively according to their specific health needs and ultimately reducing health disparities across Indonesia.

Author Contributions

Nurhanifa: Conceptualization, Methodology, Formal Analysis, Data Curation, Writing-Original Draft Preparation. Neva Satyahadewi: Data Curation, Software, Project Administration, Writing-Review and Editing. Hendra Perdana: Formal Analysis, Validation, Visualization, Supervision, Writing-Review and Editing. All authors discussed the results and contributed to the final manuscript.

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Declarations

The authors declared that they have no conflicts of interest to report study.

Declaration of Generative AI and AI-assisted Technologies

AI-assisted technology (ChatGPT) was used to support sentence restructuring and clarity improvements. The authors confirm that the underlying ideas, arguments, data analyses, and conclusions are original and were not generated by AI. All AI-assisted edits were critically reviewed and validated by the authors.

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