

Finite-Mixture Partial Least Squares Structural Equation Modeling of Multidimensional Poverty and Latent Regional Heterogeneity in Central Java

Nikita Audrey Putiray^{1*}, Fadli Ode²

¹Department of Statistics, Universitas Pattimura, Ambon, Indonesia

² Department of Statistics, Universitas Pattimura, Ambon, Indonesia

*Corresponding author: naudry2000@gmail.com

ABSTRACT

This study reformulates a historical regional-poverty application using partial least squares structural equation modeling (PLS-SEM) and finite-mixture PLS (FIMIX-PLS). The analysis covers 35 districts and municipalities in Central Java using 2025 socioeconomic indicators grouped into five latent constructs: education, health, human capital, economic conditions, and poverty. The measurement model contains 14 reflective indicators, while the recursive structural model links education to health, human capital, and economic conditions, and links human capital and economic conditions to poverty. The reported outer loadings range from 0.724 to 0.998, and all bootstrap t statistics for the indicators exceed 1.96. The poverty construct has an R -squared value of 0.552, indicating that 55.2% of its reported variance is explained by human-capital and economic-condition constructs. The strongest direct structural association with poverty is the economic-condition path (coefficient = 0.843; $t = 5.041$). FIMIX-PLS yields the highest normalized entropy at $K = 5$ ($EN = 0.955$), suggesting substantial separation among five latent regional segments. Because the raw data and original project file were not supplied, this article reproduces and critically reassesses the reported estimates rather than independently re-estimating them. The results demonstrate the statistical value of component-based structural modeling for multidimensional poverty while emphasizing the need for contemporary reliability, predictive, and segmentation checks.

Keywords: PLS-SEM; FIMIX-PLS; latent heterogeneity; multidimensional poverty; Central Java; statistical modeling

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1. INTRODUCTION

Poverty is a multidimensional development problem whose measurement extends beyond income to education, health, employment, infrastructure, vulnerability, and access to public services. Recent international assessments increasingly combine monetary and nonmonetary indicators to distinguish chronic deprivation from temporary shortfalls and to guide geographically targeted policies [1]–[6]. Indonesian evidence similarly shows that poverty persistence and transitions are associated with education, labor-market conditions, household characteristics, regional inequality, and exposure to shocks [7]–[9].

At the subnational level, the relevant indicators are strongly interrelated. Educational attainment can affect health knowledge, employability, and productivity; health conditions can affect participation in education and work; and the structure of local employment can shape both income and vulnerability. Recent Central Java and Indonesian studies continue to identify education, health, economic growth, wages, employment, and sectoral structure as important correlates of poverty [10]–[15]. A statistical framework that

estimates several relationships simultaneously is therefore preferable to a sequence of isolated regressions when the substantive concepts are latent and measured by multiple indicators.

Partial least squares structural equation modeling (PLS-SEM) is a component-based approach that combines a measurement model for latent constructs with a structural model for their relationships. Recent methodological literature emphasizes its usefulness for prediction-oriented research, complex models, small-to-moderate samples, nonnormal data, and composite or latent-variable specifications, while also stressing disciplined assessment of reliability, validity, predictive performance, and robustness [16]-[20], [21]-[28]. When observations may arise from unobserved subpopulations, latent-class extensions such as FIMIX-PLS can identify segments with distinct structural coefficients [29], [30].

This article reconstructs the reported PLS-SEM and FIMIX-PLS analysis of poverty across 35 districts and municipalities in Central Java. Its statistical objectives are to: (1) specify the reflective measurement and recursive structural models in equation form; (2) evaluate the reported indicator loadings, reliability, convergent validity, path coefficients, and explained variance; (3) examine latent regional heterogeneity through finite-mixture segmentation; and (4) interpret the historical findings using current PLS-SEM reporting standards. The numerical results are taken from the supplied manuscript; no claim of independent recomputation is made because the raw data and original SmartPLS project were unavailable.

2. LITERATURE REVIEW AND STATISTICAL FRAMEWORK

2.1 Multidimensional Poverty and Regional Development

Contemporary poverty analysis distinguishes monetary poverty from multidimensional deprivation. Global and Indonesian reports emphasize that education, health, housing, employment, social protection, and local economic opportunity jointly determine whether households can achieve and maintain minimum living standards [1]-[6]. Longitudinal Indonesian studies further distinguish chronic poverty from transient poverty and show that regional and household characteristics alter the probability of entering or escaping poverty [7], [8].

The present construct system treats education as the exogenous development foundation and models health, human capital, and economic conditions as endogenous mechanisms. Poverty is represented by the headcount index, poverty-gap index, and poverty-severity index. This specification is consistent with recent empirical work that links poverty to schooling, labor-market outcomes, economic growth, wage conditions, health, and geographic disparities in Indonesia [9]-[15].

2.2 PLS-SEM Measurement and Structural Models

PLS-SEM estimates latent-variable scores and structural coefficients through an iterative sequence of outer approximation, inner approximation, and weight updating. It is commonly used when the aim includes explaining or predicting target constructs, when the model is complex relative to the sample, or when strict covariance-based distributional assumptions are difficult to justify [16]-[20], [21]-[25]. Current guidance recommends that researchers explicitly define whether constructs are reflective or formative, report indicator reliability and construct reliability, assess convergent and discriminant validity, examine collinearity, evaluate structural paths and explained variance, and add predictive and robustness checks where possible [25]-[28].

All constructs in the historical application were specified reflectively. Under a reflective specification, indicators are treated as manifestations of a common latent construct. This assumption should be supported conceptually, because changing the measurement direction alters the meaning of the model. In the present reassessment, the historical reflective specification is retained so that the reported parameters can be reproduced faithfully.

2.3 Unobserved Heterogeneity and FIMIX-PLS

A single aggregate structural model can conceal groups of observations with different path coefficients. Latent-class procedures estimate segment membership probabilistically rather than assigning groups in advance. Recent reviews of latent-class analysis in PLS-SEM recommend comparing several segment solutions, examining information criteria, entropy, segment size, stability, and substantive interpretability rather than selecting a solution from one statistic alone [29], [30]. FIMIX-PLS is used here to evaluate whether the 35 regional units may contain statistically distinct latent segments.

Let K denote the number of latent segments, ρ_k the prior proportion of segment k , and θ_k the segment-specific parameters. The conditional density of observation i is represented as a finite mixture:

$$f(y_i | x_i, \theta) = \sum_{k=1}^K \rho_k f_k(y_i | x_i, \theta_k), \rho_k \geq 0, \sum_{k=1}^K \rho_k = 1. \quad (1)$$

Within segment k , the structural relationships are allowed to vary through segment-specific path matrices:

$$\eta_i = B_k \eta_i + \Gamma_k \xi_i + \zeta_{ik}, z_i = k. \quad (2)$$

For segment k , define the structural residual vector as the difference between the observed endogenous latent scores and their segment-specific predictions:

$$r_{ik} = (I - B_k) \eta_i - \Gamma_k \xi_i. \quad (3)$$

If the segment-specific residual vector is multivariate normal with covariance matrix Σ_k , its conditional density can be represented by the J -variate normal density ϕ_J :

$$f_k(y_i | x_i, \theta_k) = \phi_J(r_{ik}; \mathbf{0}, \Sigma_k). \quad (4)$$

The observed-data log-likelihood maximized by the finite-mixture procedure is:

$$\ell(\theta) = \sum_{i=1}^N \ln \left[\sum_{k=1}^K \rho_k f_k(y_i | x_i, \theta_k) \right]. \quad (5)$$

The posterior probability that observation i belongs to segment k follows Bayes' rule:

$$p_{ik} = \Pr(z_i = k | y_i, x_i) = \frac{\rho_k f_k(y_i | x_i, \theta_k)}{\sum_{s=1}^K \rho_s f_s(y_i | x_i, \theta_s)}. \quad (6)$$

In the expectation-maximization representation, the segment proportion is updated from the posterior membership weights:

$$\rho_k^{(t+1)} = \frac{1}{N} \sum_{i=1}^N p_{ik}^{(t)}. \quad (7)$$

Candidate segment solutions can be compared using information criteria, where q is the number of freely estimated parameters and $\ell_{\max}$ is the maximized log-likelihood:

$$\text{AIC} = -2\ell_{\max} + 2q \quad (8)$$

$$\text{BIC} = -2\ell_{\max} + q \ln(N) \quad (9)$$

$$\text{CAIC} = -2\ell_{\max} + q[\ln(N) + 1] \quad (10)$$

Normalized entropy summarizes classification certainty; values closer to one indicate clearer separation among the estimated segments:

$$\text{EN} = 1 - \frac{\sum_{i=1}^N \sum_{k=1}^K p_{ik} \ln(p_{ik})}{N \ln(K)} \quad (11)$$

These equations clarify that FIMIX-PLS does not merely cluster latent scores. It estimates segment-specific structural coefficients jointly with probabilistic membership. Accordingly, a defensible segment solution should balance statistical fit, classification quality, minimum segment size, convergence stability, and substantive interpretability [16], [29].

3. RESEARCH METHODS

3.1. Study Design and Data

The study is an ecological cross-sectional analysis of 35 districts and municipalities in Central Java. The historical manuscript states that the indicators were drawn from the 2025 National Socioeconomic Survey and National Labor Force Survey. The unit of analysis is therefore a district or municipality, not an individual

household. The sample size is small relative to many SEM applications; consequently, the results are interpreted as an exploratory component-based model and not as definitive causal evidence.

3.2. Constructs and Indicators

Five latent constructs and 14 manifest indicators were included. Education is exogenous, while health, human capital, economic conditions, and poverty are endogenous. Table 1 summarizes the operational definitions.

Table 1. Latent Constructs and Manifest Indicators

Construct	Code	Indicator	Mode
Education (ξ_1)	X ₁	School participation rate	Reflective
	X ₂	Mean years of schooling	Reflective
	X ₃	Percentage completing primary, junior secondary, senior secondary, or higher education	Reflective
Health (η_1)	Y ₁	Households using a clean drinking-water source	Reflective
	Y ₂	Households with a private latrine	Reflective
	Y ₃	First birth assisted by a health professional	Reflective
Human capital (η_2)	Y ₄	Literacy rate	Reflective
	Y ₅	Open unemployment rate	Reflective
Economic conditions (η_3)	Y ₆	Dependency ratio	Reflective
	Y ₇	Employment opportunity rate	Reflective
	Y ₈	Population aged 15+ employed in agriculture	Reflective
Poverty (η_4)	Y ₉	Headcount index (P0)	Reflective
	Y ₁₀	Poverty-gap index (P1)	Reflective
	Y ₁₁	Poverty-severity index (P2)	Reflective

3.3. Model Specification and Editable Equations

The reflective outer model relates observed indicator vectors to exogenous and endogenous latent variables:

$$x = \Lambda_x \xi + \delta, y = \Lambda_y \eta + \varepsilon. \quad (12)$$

The general inner model is:

$$\eta = B\eta + \Gamma\xi + \zeta. \quad (13)$$

For endogenous construct j , the recursive form is:

$$\eta_j = \sum_{i=1}^I \beta_{ji} \eta_i + \sum_{b=1}^B \gamma_{jb} \xi_b + \zeta_j. \quad (14)$$

The study-specific system of structural equations is:

$$\begin{cases} \eta_1 = \gamma_{11} \xi_1 + \zeta_1 \\ \eta_2 = \gamma_{21} \xi_1 + \beta_{21} \eta_1 + \zeta_2 \\ \eta_3 = \gamma_{31} \xi_1 + \beta_{32} \eta_1 + \zeta_3 \\ \eta_4 = \beta_{42} \eta_2 + \beta_{43} \eta_3 + \zeta_4 \end{cases} \quad (15)$$

For Mode A reflective blocks, an outer weight can be written as the simple-regression coefficient between indicator x_{jh} and the inner proxy z_j :

$$w_{jh} = \frac{\text{Cov}(x_{jh}, z_j)}{\text{Var}(z_j)} \quad (16)$$

For a formative Mode B block, included for methodological completeness, the multivariate weight vector is:

$$w_j = (X_j^T X_j)^{-1} X_j^T z_j \quad (17)$$

The standardized latent-variable score is formed from centered indicators:

$$y_j = \text{std}\left(\sum_{h=1}^{H_j} w_{jh}(x_{jh} - \mu_{jh})\right) \quad (18)$$

Average variance extracted (AVE) and composite reliability are evaluated as:

$$\text{AVE}_j = \frac{1}{H_j} \sum_{h=1}^{H_j} \lambda_{jh}^2 \quad (19)$$

$$\rho_{C,j} = \frac{\left(\sum_{h=1}^{H_j} \lambda_{jh}\right)^2}{\left(\sum_{h=1}^{H_j} \lambda_{jh}\right)^2 + \sum_{h=1}^{H_j} \text{Var}(\varepsilon_{jh})} \quad (20)$$

The explained variance of endogenous construct j is summarized by:

$$R_j^2 = 1 - \frac{\text{SSE}_j}{\text{SST}_j} \quad (21)$$

Bootstrap significance is assessed using the ratio of the estimated parameter to its bootstrap standard error:

$$t_{\text{boot}} = \frac{\theta}{\text{SE}_{\text{boot}}(\theta)} \quad (22)$$

The FIMIX-PLS stage applies the finite-mixture density, segment-specific structural model, likelihood, posterior membership probabilities, information criteria, and normalized entropy defined in Equations (1)-(11).

3.4. Step-by-Step Statistical Analysis

- Data preparation. Compile the 35 regional observations, verify indicator direction, inspect missing values and unusual observations, and standardize indicators where required by the software implementation.
- Model conceptualization. Define the five latent constructs, assign their reflective indicators, and specify the directional hypotheses among education, health, human capital, economic conditions, and poverty.
- Path-diagram construction. Translate the conceptual framework into a recursive PLS-SEM path diagram and verify that each endogenous construct has a valid set of antecedents.
- PLS score and parameter estimation. Iteratively estimate outer weights, latent-variable scores, loadings, path coefficients, construct means, and location parameters until the algorithm reaches convergence.
- Measurement-model evaluation. Assess indicator loadings, bootstrap t statistics, AVE, composite reliability, and Cronbach's alpha. Under current reporting practice, discriminant validity and indicator collinearity should also be examined when the raw data are available [25]-[28].
- Structural-model evaluation. Examine path signs and magnitudes, bootstrap significance, collinearity among predictors, R-squared values, effect sizes, and predictive relevance. Interpret coefficients as conditional associations, not causal effects, unless identification assumptions are independently justified.
- FIMIX-PLS segmentation. Estimate candidate solutions for $K = 2$ through $K = 6$, compare AIC, BIC, CAIC, normalized entropy, segment sizes, convergence, and substantive plausibility, and assess whether results are stable across repeated starts [29], [30].
- Interpretation and reporting. Relate the statistically supported paths and latent segments to regional poverty mechanisms, document inconsistencies or limitations in the historical output, and formulate recommendations for contemporary replication.

3.5. Decision Rules

The historical analysis used bootstrap t statistics greater than approximately 1.96 as evidence of two-sided significance at the 5% level. Loadings above 0.70 were treated as adequate, AVE above 0.50 as evidence of convergent validity, and composite reliability above 0.70 as adequate construct reliability. Contemporary guidance discourages mechanical threshold use and recommends examining theory, measurement quality, uncertainty, predictive performance, and robustness jointly [16], [20], [21]-[28].

4. RESULTS AND DISCUSSION

4.1 Measurement-Model Results

The reported reflective loadings are presented in Table 2. All loadings exceed 0.70, ranging from 0.724 for the employment-opportunity indicator to 0.998 for the poverty-gap indicator. The corresponding bootstrap t statistics are all greater than 1.96, indicating that the indicators were statistically associated with their assigned latent constructs in the reported model.

Table 2. Reported Outer Loadings and Bootstrap Statistics

Construct	Indicator	Loading	Boot. SE	t statistic	Decision
Education	X ₁	0.807	0.0392	6.361	Significant
Education	X ₂	0.969	0.0316	13.601	Significant
Education	X ₃	0.951	0.0227	17.696	Significant
Health	Y ₁	0.856	0.0732	6.262	Significant
Health	Y ₂	0.740	0.0775	3.673	Significant
Health	Y ₃	0.888	0.0491	9.102	Significant
Human capital	Y ₄	0.923	0.1122	6.715	Significant
Human capital	Y ₅	0.725	0.1294	3.243	Significant
Economic conditions	Y ₆	0.818	0.0554	8.416	Significant
Economic conditions	Y ₇	0.724	0.0621	4.100	Significant
Economic conditions	Y ₈	0.871	0.0543	9.175	Significant
Poverty	Y ₉	0.949	0.0223	15.650	Significant
Poverty	Y ₁₀	0.998	0.0102	34.745	Significant
Poverty	Y ₁₁	0.960	0.0210	15.604	Significant

4.2 Reliability and Convergent Validity

Table 3 shows AVE, composite reliability, Cronbach's alpha, and communality. Every AVE exceeds 0.50 and every composite-reliability coefficient exceeds 0.80. Cronbach's alpha is high for education and poverty, acceptable for health and economic conditions, but only 0.576 for human capital. Although composite reliability for human capital is 0.814, the low alpha indicates that internal consistency should be described as marginal rather than unequivocally reliable. The two-indicator block and the opposite conceptual directions of literacy and unemployment may contribute to this result.

Table 3. Construct Reliability and Convergent Validity

Construct	AVE	Composite reliability	Cronbach alpha	Communality
Education	0.831	0.936	0.899	0.831
Health	0.690	0.869	0.778	0.690
Economic conditions	0.651	0.847	0.741	0.651
Human capital	0.689	0.814	0.576	0.689
Poverty	0.940	0.979	0.968	0.940

Under current standards, a complete measurement assessment would additionally report HTMT or another discriminant-validity criterion, indicator and construct collinearity, confidence intervals for reliability estimates, and possibly confirmatory composite analysis [25]-[28]. These quantities could not be reconstructed from the published tables alone.

4.3 Structural-Model Results

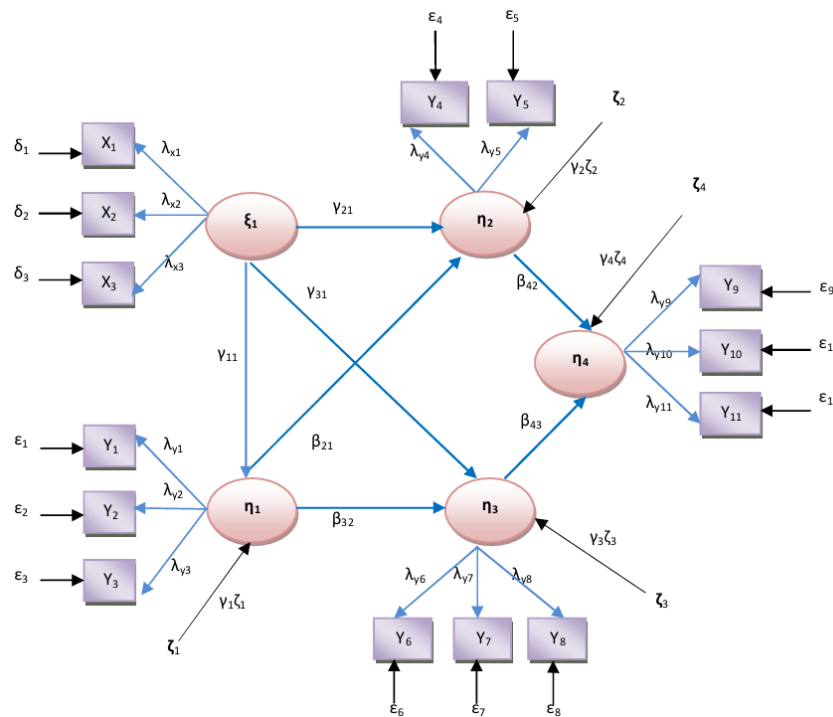


Figure 1. PLS-SEM Measurement and Structural Model for Multidimensional Poverty

The structural estimates are summarized in Table 4. Education has strong positive reported associations with health (0.748), human capital (0.836), and economic conditions in absolute magnitude (-0.629). The negative sign for the education-to-economic path requires careful attention to indicator coding because the economic block combines dependency, employment opportunity, and agricultural employment indicators that do not necessarily share the same substantive direction.

Table 4. Reported Structural Path Coefficients

Structural path	Coefficient	Boot. SE	t statistic	Decision
Education -> Health	0.748	0.0613	12.200	Significant
Education -> Human capital	0.836	0.2336	3.577	Significant
Education -> Economic conditions	-0.629	0.1914	3.287	Significant
Health -> Economic conditions	-0.147	0.2096	0.703	Not significant
Health -> Human capital	-0.304	0.2722	1.115	Not significant
Human capital -> Poverty	0.137	0.1747	0.782	Not significant
Economic conditions -> Poverty	0.843	0.1673	5.041	Significant

The reported R-squared value for poverty is 0.552. Thus, human-capital and economic-condition scores jointly account for 55.2% of the variance in the poverty construct within the fitted sample. The economic-condition path is the only statistically supported direct predictor of poverty, whereas the direct human-capital path is not significant. Because all variables are aggregated and the design is cross-sectional, these coefficients should be interpreted as model-based conditional associations rather than causal effects.

4.4 Finite-Mixture Segmentation

Candidate FIMIX-PLS solutions for two through six segments are reported in Table 5. Normalized entropy increases from 0.621 at K = 2 to 0.955 at K = 5 and then decreases to 0.932 at K = 6. On entropy alone, K = 5 provides the sharpest classification. The historical manuscript therefore selected five segments.

Table 5. Reported FIMIX-PLS Model-Selection Indices

Index	K = 2	K = 3	K = 4	K = 5	K = 6
AIC	340.342	314.778	300.356	309.587	-454.974
BIC	376.115	369.214	373.457	401.353	-344.544
CAIC	376.763	370.200	374.781	403.015	-342.544
Normalized entropy	0.6205	0.9086	0.9502	0.9550	0.9320

The segment conclusion must nevertheless be treated as provisional. The negative information-criterion values reported for K = 6 are unusual relative to the preceding solutions, and the table does not include segment sizes, convergence diagnostics, repeated-start stability, or segment-specific coefficients. Current latent-class guidance recommends triangulating entropy with information criteria, minimum segment size, stability, and substantive interpretability [29], [30]. Without the original project file, the apparent information-criterion inconsistency cannot be audited.

4.5 Statistical and Policy Interpretation

The model supports a multidimensional view of poverty in which educational conditions are linked to several intermediate development constructs and economic conditions have the strongest direct association with poverty. This pattern is broadly compatible with recent Indonesian research emphasizing education, employment, regional economic structure, and household vulnerability [7]-[15]. However, the signs of latent-variable paths depend on the coding and orientation of every indicator. The economic construct includes both potentially favorable and unfavorable measures, so it should not automatically be interpreted as a unidirectional measure of economic quality.

The five-segment FIMIX result suggests that a single provincial-average model may obscure district-level heterogeneity. In a contemporary replication, segment profiles should be mapped against urban-rural status, labor-market structure, education, health infrastructure, and geographic accessibility. Policy implications should be drawn only after segment membership is stable and segment-specific paths are validated on held-out or temporally updated data.

4.6 Limitations and Modern Reassessment

Four limitations are central. First, the analysis uses 2025 data and therefore describes historical, not current, Central Java. Second, the sample contains only 35 regional units, which constrains the stability of complex latent-class solutions. Third, raw data, software settings, bootstrap replication counts, and segment-specific output were not available for independent verification. Fourth, the original report did not include discriminant validity, collinearity, effect sizes, out-of-sample prediction, or sensitivity checks. Recent PLS-SEM recommendations place greater emphasis on these diagnostics and on transparent method-choice reporting [20], [21]-[30].

5. CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

The historical Central Java application demonstrates how PLS-SEM can combine multiple education, health, human-capital, economic, and poverty indicators in one statistical system. The reported measurement model has high loadings and satisfactory AVE and composite reliability, although the human-capital alpha of 0.576 is marginal. The structural model explains 55.2% of the variance in poverty, and economic conditions show the strongest significant direct association with poverty. FIMIX-PLS indicates the highest normalized entropy for a five-segment solution, suggesting latent regional heterogeneity, but the segment choice cannot be considered final without additional diagnostics.

5.2 Recommendations

A contemporary replication should use current district-level data, explicitly align indicator directions, reassess whether each block is reflective or formative, increase bootstrap replications, report HTMT and collinearity, evaluate effect sizes and predictive performance, and compare FIMIX-PLS with alternative latent-class or multigroup procedures. The segmentation stage should disclose segment sizes, segment-specific path coefficients, repeated-start stability, and external profiles. These additions would convert the historical exploratory result into a more reproducible and policy-relevant statistical assessment.

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ETHICS STATEMENT

The study uses aggregated secondary regional statistics and does not involve direct interaction with human participants. Ethical approval for human-subject research was therefore not applicable to the reported analysis.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Sri Sulastris: conceptualization, data curation, methodology, formal analysis, visualization, and original drafting. Muhammad Rusli B: supervision, methodological review, validation, and manuscript review.

DATA AVAILABILITY

This reformatted article is based on numerical tables and descriptions contained in the supplied historical manuscript. The underlying district-level dataset and original SmartPLS project were not included; consequently, the estimates could not be independently recomputed.

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