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Spatial Panel Data Analysis of Income Inequality, Poverty, and Human Development in Sumatra, Indonesia

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Abstract

Background: Human development disparities across Sumatra remain a regional policy concern because differences in HDI persist alongside inequality, poverty, and geographic connectivity. Previous studies have largely treated inequality and poverty as non-spatial determinants, leaving limited evidence on spatial interdependence in provincial HDI.
Objective: This study examines the effects of the Gini Ratio and poverty rate on HDI and identifies spatial dependence and clustering across Sumatra.
Methods: A balanced panel of 10 provinces for 2016–2024 (90 observations) was analyzed using panel regression with a spatial-lag component. Common Effect, Fixed Effect, and Random Effect models were compared using Chow and Hausman tests, with the Fixed Effect Model selected. A binary first-order contiguity matrix represented spatial links, and estimation was conducted in EViews.
Results: The Gini Ratio negatively and significantly affected HDI (β = -39.40173; p = 0.0001), as did poverty (β = -1.494009; $p < 0.001$). The spatial-lag coefficient was positive and significant (ρ = 0.022003; p = 0.0196), indicating positive spatial dependence. The model explained 82.93% of HDI variation (adjusted R^2 = 0.829330).
Conclusion: Inequality and poverty constrain human development, while significant spatial dependence shows that neighboring provinces are interconnected. The findings support coordinated regional policies integrating poverty reduction, income equality, and education, health, and infrastructure planning.

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INTRODUCTION

The study of economic distribution and interaction in geographical space is an important part of spatial economics which emphasizes that economic activity is not only influenced by internal factors of a region, but also by interregional linkages (Phelps, 2017; Proost & Thisse, 2019; Rahmadi et al., 2022). In the context of Indonesia, which is an archipelagic country with complex geographical characteristics, the differences in conditions between regions are becoming increasingly real, both in terms of accessibility, availability of resources, infrastructure, and economic structure (Rahmatunnisa et al., 2018; Syauqi et al., 2021).

This has led to the emergence of development disparities that are structural and tend to be persistent between regions (Cuadrado-Roura et al., 2025). Krugman & Jacob (2016) explains that spatial economics can affect regional growth through agglomeration and diffusion mechanisms, where economic activity tends to be concentrated in certain regions and spreads unevenly to other regions. This condition contributes to growth inequality which ultimately has an impact on the quality of human development and community welfare (Cerra et al., 2021; Ferreira et al., 2022; Holmes et al., 2000). Recent BPS evidence reinforces the empirical relevance of the problem: Indonesia's HDI reached 75.02 in 2024, while provincial outcomes remained heterogeneous; for example, West Sumatra recorded an HDI of 76.43 and South Sumatra 73.84 in the same year (BPS-Statistics Indonesia, 2025). Such variation indicates that improvements in national human development can coexist with persistent subnational gaps.

The island of Sumatra as one of the strategic areas in Indonesia has a very high economic, social, and cultural diversity between provinces (Withington, 1967). This difference is not only reflected in the economic structure, but also in the level of urbanization, the quality of infrastructure, as well as access to public services such as education and health (Smailov, 2026; Zhao et al., 2022). Provinces in Sumatra show significant differences in development achievements, which is ultimately reflected in the variation in the Human Development Index (HDI) value. HDI as a composite indicator of human development measures the dimensions of health, education, and decent living standards, so it is an important measure to see the quality of development of a region. However, HDI does not stand alone, but is influenced by various structural factors, including income inequality and poverty levels. Sumatra deserves specific academic attention because its provinces are economically connected through trade corridors, labor mobility, and shared infrastructure while simultaneously displaying heterogeneous human-development outcomes. This combination creates a setting in which provincial HDI may not be spatially independent, so a neighboring province's development conditions can become empirically relevant to another province's outcome.

In this context, the Gini Ratio is an important indicator to describe the level of inequality in income distribution between populations. High inequality shows that development outcomes are not evenly distributed, so only a small part of society enjoys economic growth (Bilan et al., 2020; Charles et al., 2022). This condition has the potential to hinder the improvement of the quality of life of the community at large. Research by Farhan & Sugianto (2022) shows that the Gini Ratio has a negative influence on HDI, which means that increasing inequality will reduce human development achievements. Thus, the equitable distribution of income is one of the important prerequisites in improving the quality of human development. The earlier findings are directionally consistent, but they do not establish whether the inequality-HDI relationship changes when cross-provincial dependence is explicitly modeled. This distinction is important because a coefficient estimated under spatial independence may confound within-province effects with regional spillovers.

In addition to inequality, poverty levels are also a key variable in explaining the variation in HDI between regions. Poverty reflects not only low incomes, but also limited access to education, health services, decent work, and basic infrastructure. The high level of poverty shows that some people have not fully enjoyed the results of development, thus having a direct impact on the low quality of human resources. Various studies such as Sitompul et al. (2023) confirm that poverty has a negative influence on HDI, where an increase in poverty will significantly reduce the human development achievement of a region. The literature therefore supports a negative poverty-HDI relationship, yet most evidence cited above treats provinces as independent observations. Recent Indonesian spatial studies likewise show that poverty and human-development outcomes can exhibit geographic dependence, suggesting that non-spatial specifications may understate regional interaction ('Iffah et al., 2023; Sari & Tiwari, 2024).

Furthermore, a spatial perspective is necessary because geographically connected provinces can influence one another through labor mobility, trade, investment, infrastructure networks, and policy diffusion. Conventional panel regression assumes that, conditional on observed covariates and effects, observations do not retain systematic spatial dependence. When neighboring HDI outcomes are correlated, that assumption can be restrictive and may obscure spillover mechanisms. Spatial panel regression therefore extends the conventional panel framework by explicitly incorporating the spatially lagged HDI term, allowing the study to test whether human-development outcomes cluster across neighboring provinces rather than merely assuming that such interaction exists.

Based on this gap, the study integrates panel-data estimation with an explicit spatial component to examine Gini Ratio, poverty, and HDI across all 10 provinces in Sumatra during 2016–2024. The novelty lies in jointly estimating socioeconomic determinants and interprovincial HDI dependence within a balanced provincial panel, then interpreting both coefficient effects and spatial clustering for regional policy. The study addresses two objectives:

(1) to estimate the effects of income inequality and poverty on provincial HDI while accounting for spatial dependence, and (2) to identify the spatial pattern of human development across Sumatra. Consistent with spatial-development theory and prior empirical evidence, the hypotheses are: H1, a higher Gini Ratio is associated with lower HDI; H2, a higher poverty rate is associated with lower HDI; and H3, provincial HDI exhibits positive spatial dependence across neighboring provinces.

METHOD

The study used a quantitative explanatory design with balanced panel data for the 10 provinces of Sumatra over 2016–2024, yielding 90 province-year observations. The period was selected to provide a nine-year series that is sufficiently long for panel estimation while maintaining comparability of the provincial indicators used in the analysis through the most recent year covered by the study. Secondary data on the Human Development Index, Gini Ratio, and poverty rate were obtained from publications and official statistical series of the Central Statistics Agency (BPS). The analysis compared the Common Effect Model (CEM), Fixed Effect Model (FEM), and Random Effect Model (REM) before estimating the spatially augmented panel specification. The empirical analysis was conducted in EViews.

Model selection was conducted sequentially using the Chow test to compare CEM and FEM and the Hausman test to compare FEM and REM; both tests supported the Fixed Effect Model. Spatial interaction was represented by a binary first-order contiguity matrix, W, coded 1 for provinces treated as directly adjacent in the study's geographic network and 0 otherwise. This contiguity specification was preferred to inverse-distance weighting because the research question concerns immediate neighboring spillovers and requires an interpretable regional adjacency structure. The spatial term W(HDI) was then included to estimate the association between a province's HDI and the HDI of its connected neighbors. Coefficient significance was evaluated using t-tests, overall model significance using the F-test, and explanatory power using R^2 and adjusted R^2. Rather than assuming that panel data automatically remove classical problems, model diagnostics were interpreted cautiously. In particular, the reported Durbin-Watson statistic of 0.966089 indicates possible serial correlation; because the available original output does not report a formal Wooldridge test, cross-sectional-dependence test, Moran's I, or spatial Lagrange Multiplier diagnostic, the spatial inference is limited to the estimated spatial coefficient and this diagnostic limitation is explicitly acknowledged.

$$HDI_t = \beta_0 + \beta_1 GR_t + \beta_2 PR_t + \rho\, W(HDI)_t + e_t$$

Description :
HDI = Human Development Index
GR = Gini Ratio
PR = Poverty Rate
W = Spatial Matrix (weight) Based on Distance Between Provinces (1 = near/ directly bordering) and 0 = distant/not directly bordering)
W(HDI) = Spatial Variable (spatial effect) of each province's HDI
β_0 = Constant
β_1, β_2 = Regression Coefficient
ρ = Regression Coefficient of Spatial Effects Between Provinces (Spatial Autocorrelation)
e_t = Error Term

The calculation of the spatial effect coefficient between provinces uses the following provisions (Anselin, 2004):

1. If the value $\rho > 0$, then there is a positive spatial autocorrelation. This means that provinces with high HDI are adjacent to other provinces that have high HDI.
2. If the value $\rho < 0$, then there is a negative autocorrelation. This means that provinces with high HDI tend to be close to other provinces with low HDI.
3. If the value $\rho = 0$, then there is no spatial autocorrelation. This means that the provincial HDI is random (it does not have a clear pattern).

Spatial effects (spatial variables) have the following conditions: 1) If the W (HDI) value is high, then the province has a high HDI adjacent to other provinces with a high HDI and there is a spatial cluster of high HDI in the area. 2) If the W (HDI) value is low, then the province of low HDI is adjacent to other provinces with low HDI and there are spatial clusters of low HDI in the area. 3) If the W (HDI) value is moderate/heterogeneous, then the province has HDI adjacent to one/two other provinces with high/low HDI.

RESULTS AND DISCUSSION

Results

Best Model Selection

The effect of Gini Ratio, poverty level and spatial effects on HDI in all provinces in Sumatra during 2016-2024 was carried out using three panel data regression approaches. The results of the calculation were then tested to select the best model and later used as a model for estimating regression equations. The results of the best model selection test are:

Table 1

Summary of Chow Test Results

Redundant Fixed Effects Tests			
Pool: Untitled			
Test cross-section fixed effects			
Effects Test	Statistic	D.F.	Prob.
Cross-section F	37.091950	(9,77)	0.0000
Cross-section Chi-square	150.693130	9	0.0000

Source : data processed 2026

The results of Chow's test showed that the Cross-section Chi-square had a Statistic value = 150.693130 and Prob. = 0.0000 < 0.05, meaning that the Fixed Effects model was the best model to choose over the Common Effects (PLS) model.

Table 2

Summary of Hausman's Test Results

Correlated Random Effects - Hausman Test			
Pool: Untitled			
Test cross-section random effects			
Test Summary	Chi-Sq. Statistic	Chi-Sq. D.F.	Prob.
Cross-section random	77.409559	3	0.0000

Source : data processed 2026

The test results showed that the Cross-section random Chi-Sq Statistic value = 77.409559 and Prob. = 0.0000 < 0.05, meaning that the Fixed Effects model is the best and the best compared to the Random Effects model. There are two tests to test the results above, namely the Chow and Hausman tests that give the same results and choose the Fixed Effect model. This means that this model is selected and the model used as a regression equation estimation.

Estimation of Panel Data Regression Equations

The best and chosen equation for the regression results of the panel data is the Fixed Effects Model. Based on the regression output in table 3, the regression equation can be made as follows:

$$IPMt = 94.39875 - 39.40173\ GR_t - 1.494009\ TK_t + 0.022003\ W(IPM)_t$$

The calculation of the estimated coefficient value of the regression equation above can be interpreted as follows:

1. The constant value is 94.39875, meaning that if the Gini ratio, poverty level and spatial effect do not change or are considered constant, then the average HDI of all provinces in Sumatra

is 94.39875.
2. The value of the Gini ratio regression coefficient – 39.40173, means that every increase in Gini ratio of 1 unit will decrease the HDI by 39.40173 units in the provinces in Sumatra assuming that other variables remain with the Prob. 0,0001. Substantively, this negative coefficient supports the proposition that unequal distribution of development benefits can weaken access to education, health, and living-standard improvements for lower-income groups. Because the Gini Ratio ranges on a bounded scale, the one-unit interpretation is primarily mathematical; policy interpretation should focus on smaller realistic changes in inequality.
3. The value of the poverty rate regression coefficient – 1.494009, means that every increase in the poverty level of 1 unit will reduce the HDI of 1.494009 units in the provinces in Sumatra assuming that other variables remain with the Prob. 0.0000. The result is consistent with the multidimensional mechanism of poverty: higher poverty constrains household capacity to finance schooling, nutrition, preventive health care, and other investments that directly enter or support HDI dimensions.
4. The value of the spatial effect regression coefficient (ρ) is 0.022003, meaning that every increase in the spatial effect of 1 unit will increase the HDI of 0.022003 units in each province in Sumatra assuming that other variables remain with Prob. 0.0196. The positive sign indicates that human-development outcomes are not isolated across provinces; higher HDI in connected provinces is associated with higher HDI locally, consistent with regional diffusion through economic linkages, service access, and infrastructure networks. The p-value of 0.0196 confirms statistical significance at the 5% level.

Table 3
Fixed Effects Model Regression Results

Dependent Variable: IPM
Method: Panel Least Squares
Date: 02/13/26 Time: 21:09
Sample: 2016 2024
Periods included: 9
Cross-sections included: 10
Total panel (balanced) observations: 90

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	94.39875	3.763287	25.08412	0.0000
Gini Ratio	-39.40173	9.644291	-4.085497	0.0001
Q.Poverty	-1.494009	0.174124	-8.580122	0.0000
W(IPM)	0.022003	0.009227	2.384602	0.0196
	Effects Specification			
Cross-section fixed (dummy variables)				
R-squared	0.852342	Mean dependent var		72.41733
Adjusted R-squared	0.829330	S.D. dependent var		2.425716
S.E. of regression	1.002116	Akaike info criterion		2.974989
Sum squared resid	77.32616	Schwarz criterion		3.336072
Log likelihood	-120.8745	Hannan-Quinn crister.		3.120599
F-statistic	37.03964	Durbin-Watson stat		0.966089
Prob(F-statistic)	0.000000			

Source: data processed 2026

Hypothesis Test and Coefficient of Determination (r^2)

To test the direction of the relationship and the level of significance of independent variables to the verifiable dependent together (overall) and individual (partial) according to Gujarati & Porter (2010) was carried out using the t-test and the statistical F-test.

The t-test showed that the Gini ratio and poverty level had a negative and significant effect on HDI with a Prob. value of < 0.05. Meanwhile, spatial effects have a positive and significant effect on HDI with a Prob value. < 0.05. In the F test, it was obtained that the Gini ratio, poverty level and spatial effect on HDI had a significant effect on the HDI of the entire province in Sumatra, where the Prob (F-statistic) was 0.000000 < 0.05. The ability of independent variable variation to change dependent variables obtained a determination coefficient value (Adjusted R-squared) of 0.829330. This means that 82.29% variation of HDI variables can be explained by the variables Gini ratio, poverty level and spatial effects in the regression model with good or high categories. (Gujarati & Porter, 2010). Meanwhile, 17.71% of variations were explained as variables outside the model. The Durbin-Watson statistic of 0.966089, however, suggests possible positive serial correlation in the residual structure. Accordingly, coefficient significance should be interpreted together with this diagnostic caution rather than as evidence that all error-dependence concerns have been eliminated.

Spatial Weight and Spatial Variable Matrix

The spatial weight matrix (W) operationalizes interprovincial dependence using a binary first-order contiguity structure. Each off-diagonal element equals 1 when two provinces are defined as immediate neighbors in the study network and 0 otherwise, while diagonal elements are 0 to exclude self-neighboring effects. Multiplying W by the HDI vector produces W(HDI), which summarizes neighboring HDI exposure for each province-year. The binary specification emphasizes direct regional interaction and keeps the interpretation consistent with the study's spillover objective.

Table 4

Spatial Weight Matrix Results (W)

Province	A	SB	SB	R	JB	SS	BK	LP	BB	KP
A	0	1	0	0	0	0	0	0	0	0
SB	1	0	1	1	0	0	0	0	0	0
SB	0	1	0	1	1	0	1	0	0	0
R	0	1	1	0	1	0	0	0	0	1
JB	0	0	1	1	0	1	1	0	0	0
SS	0	0	0	0	1	0	1	1	1	0
BK	0	0	1	0	1	1	0	1	0	0
LP	0	0	0	0	0	1	1	0	0	0
BB	0	0	0	0	0	1	0	0	0	0
KP	0	0	0	1	1	0	0	0	0	0

Source: data processed 2026

Description:

A = Aceh SU = North Sumatra SB = West Sumatra R = Riau JB = Jambi SS = South Sumatra BK = Bengkulu LP = Lampung BB = Bangka Belitung KP = Riau Islands

The weights of the spatial matrix are then used to determine the value of the spatial variable as seen in table 5.

Table 5

Spatial Variable Results (W.HDI)

Year/ Province	A	SB	SB	R	JB	SS	BK	LP	BB	KP
2016	70,00	211,93	280,15	284,34	353,65	276,15	276,40	137,73	68,40	140,82
2017	70,57	213,60	286,25	284,34	356,29	278,18	278,34	138,81	68,86	141,78
2018	71,18	215,36	359,75	288,40	359,04	280,98	280,79	140,03	69,39	143,09
2019	71,74	217,29	287,21	290,87	362,10	283,74	283,24	141,23	70,02	144,26
74,51	71,77	217,08	287,17	291,03	362,09	283,85	283,37	141,41	70,01	144,00
2021	72,00	217,77	288,21	292,07	363,26	284,86	284,42	141,88	70,24	144,57
2022	74,51	223,72	295,75	301,26	374,25	292,08	292,54	146,16	72,48	147,56
2023	75,13	225,29	298,11	376,76	377,15	294,60	295,03	147,48	73,18	148,68
2024	75,76	227,46	300,7	306,44	380,74	296,95	297,76	148,75	73,84	150,03
Average	**72,52**	**218,83**	**298,14**	**301,72**	**365,40**	**285,71**	**285,77**	**142,61**	**70,71**	**144,98**

Source: data processed 2026

Based on the results of the calculation of the average W(HDI) during the period of 2016-2024, it can be explained as follows:

1. Aceh Province has a low HDI value and is adjacent to North Sumatra Province which has a high HDI.
2. North Sumatra Province has a high HDI value and is adjacent to Aceh Province with a low HDI and West Sumatra which has a high HDI.
3. West Sumatra Province has a high HDI value and is adjacent to the provinces of North Sumatra, Riau and Jambi which have high HDI.
4. Riau Province has a high HDI value and is adjacent to the provinces of North Sumatra, West Sumatra, Jambi and the Riau Islands which have high HDI.
5. Jambi Province has a high HDI value and is adjacent to the provinces of West Sumatra, Riau, South Sumatra and Bengkulu which have high HDI.
6. South Sumatra Province has a high HDI value and is adjacent to the provinces of Jambi, Bengkulu and Lampung which have high HDI and Bangka Belitung with low HDI.
7. Bengkulu Province has a high HDI value and is adjacent to the provinces of West Sumatra, Jambi, South Sumatra and Lampung which have high HDI.
8. Lampung Province has a high HDI value and is adjacent to South Sumatra and Bengkulu Provinces which have high HDI.
9. Bangka Belitung Province has a low HDI value and is adjacent to South Sumatra Province which has a high HDI.
10. Riau Islands Province has a high HDI value and is adjacent to Riau and Jambi Provinces which have high HDI.

Discussion

The Effect of Gini Ratio and Poverty Rate on Provincial HDI in Sumatra by Considering Spatial Effects

The spatial effect is the emergence of the influence of interaction between provinces in Sumatra that have close distances. Based on the spatial regression equation, the spatial effects of the entire province in Sumatra can be known as direct effects, indirect effects and total effects. The results are:

Table 6

Spatial Effects of All Provinces in Sumatra

Effect	Variable		Spatial Effects (ρ)
	Gini Ratio	Poverty Rate	
Direct	- 39,40173	- 1,494009	0,022003
Indirect	-0,86696	-0,03287	
Total	-40,2687	-1,52688	

Source : data processed 2026

The estimated spatial coefficient is positive and statistically significant ($\rho = 0.022003$; $p = 0.0196$), indicating positive spatial dependence rather than an insignificant effect. Provinces with relatively high HDI therefore tend to be connected to provinces with similarly high human-development outcomes. This pattern is consistent with spatial-economics theory: development benefits can diffuse through labor markets, trade links, transport infrastructure, educational access, health-service networks, and policy learning. The result also supports recent evidence that Indonesian development and poverty outcomes are geographically interdependent 'Iffah et al. (2023) and aligns with Sari & Tiwari (2024), who emphasize substantial subnational spatial heterogeneity in Indonesian human capital.

The negative Gini Ratio coefficient ($\beta = -39.40173$; $p = 0.0001$) shows that greater income inequality is associated with lower human development after controlling for province fixed effects, poverty, and the spatial term. This result is consistent with Farhan & Sugianto (2022), but the present study extends those findings by showing that the relationship persists within a spatially connected provincial system. The poverty coefficient is also negative and significant ($\beta =$

-1.494009; p < 0.001), supporting (Sitompul et al., 2023). The mechanism is substantively plausible because poverty restricts household access to schooling, health care, adequate nutrition, and decent living conditions, while inequality can limit the extent to which regional growth translates into broadly shared capabilities. Together, the findings indicate that improving HDI requires not only aggregate economic expansion but also distribution-sensitive and poverty-oriented development strategies.

Spatial Patterns of the Influence of Gini Ratio and Poverty Levels on Provincial HDI in Sumatra

The spatial pattern in Table 7 indicates that most Sumatra provinces are embedded in high-HDI clusters, while Aceh and Bangka Belitung display more heterogeneous neighboring configurations. The scientific implication is that provincial human development should be analyzed as a regional system rather than as ten independent policy units. High clusters may reflect cumulative advantages in connectivity, public-service provision, labor mobility, and economic integration, whereas heterogeneous provinces may face weaker transmission of those benefits or different local constraints. For policymakers, the results support three targeted actions: coordinate education and health-service planning across provincial borders; prioritize poverty reduction and inclusive-income programs in provinces that lag behind neighboring clusters; and use interprovincial infrastructure and labor-market cooperation to strengthen positive spillovers. For regional-economics research, the findings demonstrate that incorporating spatial dependence can change the interpretation of socioeconomic determinants by distinguishing within-province effects from regional interaction.

Table 7

Provincial Spatial Patterns in Sumatra

Province	Spatial Pattern (W.IPM)	Remarks
A	Moderate	High SU HDI
	Moderate	Low HDI A
SB	High Cluster	High HDI SB
SB	High Cluster	High HDI of SU, R and JB
R	High Cluster	IPM SU, SB, JB and DG Tinggi
JB	High Cluster	IPM SB, R, SS and BK Tinggi
		High IPM JB, BK, LP and Low
SS	High Cluster	BB
	Moderate	Low BB HDI
BK	High Cluster	IPM SB, JB, SS and LP Tinggi
LP	High Cluster	High HDI SS and BK
BB	Moderate	High SS HDI
KP		High HDI R and JB
	High Cluster	

Source : data processed 2026

CONCLUSION

The study finds that income inequality and poverty are both negatively and significantly associated with provincial HDI in Sumatra, with coefficients of -39.40173 (p = 0.0001) and -1.494009 (p < 0.001), respectively. The spatial coefficient is positive and significant (ρ = 0.022003; p = 0.0196), showing that HDI outcomes are interdependent across connected provinces rather than spatially random. The fixed-effect specification explains a substantial share of HDI variation (adjusted R^2 = 0.829330). Thus, the study's main contribution is to show that inequality, poverty, and interprovincial spatial dependence jointly matter for understanding human development in Sumatra. The theoretical implication is that regional human development is shaped by both local socioeconomic conditions and geographic interaction, while the policy implication is that poverty and inequality reduction should be coordinated with cross-provincial planning. The principal limitation is that the available model output does not include formal Moran's I, spatial LM, cross-sectional-dependence, or serial-correlation tests; the reported Durbin-Watson statistic also warrants caution. Future research should test alternative spatial-weight matrices, apply formal spatial diagnostics and robust estimators, and incorporate additional determinants such as education spending, health infrastructure, GRDP per capita, and interregional connectivity.

Provincial governments should translate the positive spatial linkage into coordinated regional action by aligning education and health services in border areas, developing interoperable transport and service networks, and jointly targeting poverty pockets that may weaken surrounding provinces. Provinces with lower or heterogeneous HDI patterns should receive differentiated interventions focused on household income security, school participation, health access, and inclusive employment, while high-HDI clusters should be used as regional anchors for policy diffusion and interprovincial learning.

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AUTHOR CONTRIBUTION STATEMENT

Selamet Rahmadi was solely responsible for the conceptualization, research design, methodology, data collection, data analysis, interpretation of results, literature review, visualization, manuscript preparation, and critical revision of the study. The author also approved the final version of the manuscript and assumes full responsibility for the accuracy, integrity, and scholarly content of the work.

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