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Interregional Poverty Linkages and Human-Capital Correlates in the Special Region of Yogyakarta: Evidence from a Spatial Panel Model

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ABSTRACT

Poverty remains unevenly distributed across the Special Region of Yogyakarta (DI Yogyakarta), suggesting that local conditions and interregional linkages may shape poverty outcomes. This study examined poverty rates across five regencies/city administrative units in DI Yogyakarta during 2021–2025 while accounting for spatial dependence. A balanced panel was analyzed by comparing common, fixed, and random effects models, followed by spatial diagnostics and estimation of a spatial autoregressive fixed-effects model. The average poverty rate declined from 13.28% in 2021 to 10.61% in 2025. Under model-based inference, the spatial lag coefficient was positive (ρ=0.629), indicating spatial association in poverty rates across neighbouring regions. The spatial impact decomposition showed that expected years of schooling had negative direct, indirect, and total effects on poverty, whereas the effects of mean years of schooling, literacy rate, life expectancy at birth, and stunting prevalence were weaker. The findings are interpreted as exploratory, context-specific associations.

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1. INTRODUCTION

Poverty remains a major development concern because it limits access to education, healthcare, adequate housing, nutrition, and economic opportunities [1], [2]. The issue remains particularly relevant in the Special Region of Yogyakarta, hereafter referred to as DI Yogyakarta. In March 2024, approximately 445.55 thousand people, or 10.83% of the provincial population, were living below the poverty line [3]. Although poverty has gradually declined, it remains unevenly distributed across the province. Kulon Progo and Gunungkidul consistently record higher poverty rates than Sleman and Yogyakarta City, indicating that provincial averages may conceal persistent local disparities.

Education and health are important dimensions of multidimensional poverty and human-capital development [1]. In this context, educational attainment affects access to employment and income-generating opportunities, while health and nutritional conditions influence people's ability to participate productively in economic and social activities [4], [5]. In DI Yogyakarta, disparities in human-capital outcomes, including learning achievement and childhood stunting, suggest the need to examine education and health indicators jointly [6]. This study therefore considers mean years of schooling, expected years of schooling, and literacy rate as education indicators, while life expectancy at birth and stunting prevalence represent health and nutritional conditions.

Regional poverty may also be spatially connected. Labour mobility, access to schools and healthcare facilities, infrastructure, markets, and economic activities may link neighbouring areas, so poverty in one region may be associated with poverty conditions in nearby regions. Previous studies have shown that poverty may display spatial dependence and spatial heterogeneity [7], [8]. Indonesian studies have applied panel and spatial-panel methods to poverty analysis in several regional settings. Indrasetianingsih and Wasik used panel regression to examine poverty in Madura [9], while Rizki and Taqiyyuddin applied a Spatial Autoregressive Fixed Effect Model to poverty in West Java [10]. More recent studies have also employed spatial-panel approaches to analyse poverty patterns and spatial dependence in West Java and related regional contexts [11], [12]. However, most existing studies focus on broader geographical systems and often emphasize macroeconomic, fiscal, investment, infrastructure, or demographic variables. Evidence remains limited for DI Yogyakarta, a compact province with only four regencies and one city but strong interregional socioeconomic connections.

Therefore, this study aims to examine the associations of education and health indicators with poverty rates across the regencies and city of DI Yogyakarta during 2021–2025 while accounting for regional fixed effects and spatial dependence. The study compares common, fixed, and random effects models, conducts spatial diagnostics, and estimates a spatial autoregressive fixed-effects panel model using a Queen contiguity matrix. Its contribution is to provide district-level evidence on interregional poverty linkages and human-capital correlates within DI Yogyakarta to support coordinated poverty reduction policies across administrative boundaries.

2. RESEARCH METHOD

2.1. Study Scope and Data Structure

This study used a balanced regional panel covering the four regencies and one city in DI Yogyakarta during 2021–2025, resulting in 25 region-year observations. The five cross-sectional units represent the complete set of regency- and city-level administrative areas within the province rather than a sample from a larger population. Therefore, the study is designed as a province-specific analysis of poverty variation and spatial linkages in DI Yogyakarta. Because the panel contains only five spatial units observed over five years, the results are interpreted as context-specific associations within the observed region and period, not as causal effects or nationally generalizable estimates. Particular attention is given to the stability of coefficient directions, spatial dependence, residual diagnostics, and consistency across alternative specifications, rather than relying solely on statistical significance or model fit measures.

2.2. Research Variables

The dependent variable in this study is the poverty rate, measured as the percentage of people living below the official poverty line in each regency/city. The explanatory variables represent the education, health, and nutrition dimensions of human-capital development. Education is represented by mean years of schooling, expected years of schooling, and literacy rate, which reflect accumulated educational attainment, future schooling opportunities, and basic literacy capabilities, respectively. These indicators are closely associated with socioeconomic status and the intergenerational transmission of poverty [13], [14]. Health and nutrition are represented by life expectancy at birth and stunting prevalence. Life expectancy at birth reflects the overall health conditions of the population and is closely related to socioeconomic welfare and poverty [15], whereas stunting prevalence represents chronic nutritional deprivation associated with poverty, household wealth, and educational inequalities [16]. Overall, these variables were selected because education, health, and nutrition are closely related to multidimensional poverty and human-capital development [1], [6].

Table 1. Definitions, Units, and Sources of Research Variables

Variable	Symbol	Definition	Unit	Frequency	Data Source
Poverty rate	Poverty	Percentage of the population living below the official poverty line in each regency/city	Percent	Annual	Statistics Indonesia–DI Yogyakarta
Mean years of schooling	RLS	Average number of years of formal education completed by the population aged 25 years and above	Year	Annual	Statistics Indonesia–DI Yogyakarta
Expected years of schooling	HLS	Expected number of years of schooling that a seven-year-old child is likely to complete under prevailing enrolment patterns	Year	Annual	Statistics Indonesia–DI Yogyakarta
Literacy rate	AMH	Percentage of the population within the specified age group who can read and write a simple sentence	Percent	Annual	Statistics Indonesia–DI Yogyakarta
Life Expectancy	UHH	Average estimated number of years of life a newborn is expected to live in a given year	Year	Annual	Statistics Indonesia–DI Yogyakarta
Stunting prevalence	Stunting	Percentage of children under five whose height-for-age is below the applicable nutritional standard	Percent	Annual	Ministry of Health/SSGI

2.3. Analytical Methods

The analysis was conducted in four stages. First, descriptive statistics and visual exploration were used to summarize poverty patterns and the distribution of education and health indicators across DI Yogyakarta during 2021–2025. Second, nonspatial panel data models were estimated to identify the appropriate baseline specification before incorporating spatial dependence. Following the panel-data regression framework, three standard specifications were compared: the Common Effects Model (CEM), Fixed Effects Model (FEM), and Random Effects Model (REM) [17], [18]. The CEM assumes that the intercept and slope coefficients are homogeneous across regions and years, while the FEM allows the intercept to vary across regions in order to control for unobserved time-invariant regional characteristics [19], [20]. The REM treats regional heterogeneity as part of the random error structure and is appropriate when unobserved regional effects are assumed to be uncorrelated with the explanatory variables [21]. Model selection was conducted using the Panel F or Chow test to compare CEM and FEM, the Hausman test to compare FEM and REM, and the Breusch–Pagan Lagrange Multiplier test to compare CEM and REM. These tests were used to determine whether pooled, fixed-effects, or random-effects specifications provided the most appropriate nonspatial baseline model.

Third, spatial dependence was evaluated after the preferred nonspatial panel specification had been selected. The LM-lag and LM-error tests were applied to the within-transformed fixed-effects model using splm::slmtest(). This procedure accounts for time-invariant regional heterogeneity before testing whether spatial dependence is better represented through a spatially lagged dependent variable or spatially correlated errors [22], [23]. Because the panel contains only five spatial units observed over five years, all specification tests were interpreted cautiously as exploratory model-selection evidence rather than definitive finite-sample inference.

The primary spatial weights matrix was constructed using first-order Queen contiguity, in which two regions were considered neighbours when their administrative boundaries shared at least one point. The binary adjacency matrix was then row-standardized so that the nonzero weights in each row summed to one. The spatial units were ordered as Kulon Progo, Bantul, Gunungkidul, Sleman, and Yogyakarta City. In the panel setting, the same spatial weights matrix was applied to each annual cross-section, which is equivalent to using the block-diagonal matrix $W_{NT} = I_T \otimes W_N$ where I_T is the T×T identity matrix and W_N is N×N spatial weights matrix.

Fourth, the final spatial-panel model was estimated. Because the LM-lag test supported spatial lag dependence while the LM-error test did not support spatial error dependence, the main model used a Spatial Autoregressive Fixed Effects Model (SARFEM). The model is expressed as

$$y_{it} = \rho \sum_{j=1}^{N} w_{ij} y_{jt} + X_{it}\beta + \alpha_i + \varepsilon_{it} \tag{1}$$

where y_{it} is the poverty rate in region i and year t, w_{ij} is the element of the row-standardized spatial weights matrix, ρ is the spatial lag coefficient, X_{it} is the vector of education and health indicators, β is the vector of slope coefficients, α_i denotes regional fixed effects, and ε_{it} is the error term.

Because the SAR specification includes a spatially lagged dependent variable, the raw slope coefficients do not directly represent the marginal effects of the explanatory variables. Following the partial-derivatives approach of LeSage and Pace [24], as implemented and discussed for spatial panel models by Elhorst [25], [26], the marginal effect of explanatory variable x_r is obtained from

$$S_r(W) = (I - \rho W)^{-1}\beta_r \quad (2)$$

where W is the row-standardized spatial weights matrix and ρ is the spatial lag coefficient. The average direct effect is calculated as the average diagonal element of $S_r(W)$, the average total effect is calculated as the average row sum of $S_r(W)$, and the average indirect effect is obtained as the difference between the total and direct effects. Direct effects represent within-region marginal associations, whereas indirect effects represent spatial spillover associations transmitted through neighbouring regions.

Potential endogeneity was considered because education, health, and poverty may be jointly determined. Educational and health conditions may be associated with poverty, while persistent poverty may also restrict access to schooling, healthcare, and adequate nutrition. Regional fixed effects control for unobserved time-invariant regional characteristics, but they do not fully eliminate reverse causality or omitted time-varying confounding. Therefore, the estimated relationships are interpreted as conditional associations rather than causal effects. To assess robustness, the SARFEM was re-estimated using alternative spatial weights matrices, namely Rook contiguity and inverse-distance weights. The same dependent variable, explanatory variables, fixed-effects structure, sample period, and estimator were retained across specifications; only the spatial weights matrix was changed. A one-year-lagged regressor specification was also estimated to reduce contemporaneous simultaneity, although it was not treated as a causal identification strategy.

All statistical analyses were conducted in R version 4.5.3. Nonspatial panel models were estimated using the `plm` package, while spatial weights construction, spatial diagnostics, and spatial-panel estimation were conducted using the `spdep` and `splm` package. The final SARFEM was estimated using `spml()` with `model = "within"`, `effect = "individual"`, `lag = TRUE`, and `spatial.error = "none"`. Standard errors were model-based asymptotic standard errors obtained from the numerical Hessian of the maximum-likelihood estimator. Because the panel contains only five spatial units observed over five years, the reported standard errors, p-values, and spatial impact estimates are interpreted cautiously as exploratory model-based evidence rather than definitive finite-sample inference.

Statistical inference for the spatial-panel estimator relies on model-based asymptotic standard errors derived under large-sample conditions. Because this study includes only five spatial units observed over five years, these conditions are unlikely to be well approximated. Recent methodological studies on fixed-effects spatial-panel models indicate that short panels may require special inference procedures and that conventional first-order asymptotic inference can be unreliable in finite samples [27]. Therefore, the reported hypothesis tests, standard errors, p-values, and spatial impact estimates are treated as exploratory rather than definitive. Interpretation emphasizes coefficient direction and magnitude, spatial diagnostics, and consistency across robustness specifications. Moreover, because fixed effects do not fully eliminate reverse causality or omitted time-varying confounding, the estimated relationships are interpreted as context-specific conditional associations rather than causal effects [28].

3. RESULT AND ANALYSIS

3.1. Data Description

Descriptive analysis was first conducted to summarize poverty trends and the distribution of education and health indicators across DI Yogyakarta during 2021–2025.

Table 2. Poverty Rates in DI Yogyakarta, 2021-2025

Year	Average	Minimum (%)	Maximum (%)
2021	13.28	7.64	18.38
2022	11.78	6.62	16.39
2023	11.44	6.49	15.64
2024	11.24	6.26	15.62
2025	10.61	6.14	14.53

Table 2 shows that poverty rates in DI Yogyakarta declined during 2021–2025. The average poverty rate decreased from 13.28% in 2021 to 10.61% in 2025, representing a reduction of 2.67 percentage points. The maximum and minimum poverty rates also declined, indicating a general improvement across the observed regions. However, the gap between the highest and lowest poverty rates remained substantial, narrowing only from 10.74 percentage points in 2021 to 8.39 percentage points in 2025. Thus, although poverty decreased overall, regional disparities persisted and justify further analysis of education, health, and spatial dependence.

Table 3. Descriptive Statistics of Panel Variables in DI Yogyakarta, 2021–2025

Variable	N	Mean	Std. deviation	Minimum	Maximum
Poverty rate (%)	25	11.67	4.15	6.14	18.38
Mean years of schooling, RLS (years)	25	9.89	1.64	7.30	12.13
Expected years of schooling, HLS (years)	25	15.55	1.59	12.98	17.67
Literacy rate, AMH (%)	25	95.52	3.64	88.14	99.91
Life expectancy at birth, UHH (years)	25	74.95	0.61	73.89	76.05
Stunting prevalence (%)	25	14.43	5.21	4.29	23.50

Note: Statistics are calculated from the pooled balanced panel of five regencies/city observed annually from 2021 to 2025.

Table 3 presents the descriptive statistics of the variables used in the balanced panel. The poverty rate averaged 11.67%, with values ranging from 6.14% to 18.38%, indicating substantial regional variation. The education indicators also varied across regions and years, with mean years of schooling averaging 9.89 years, expected years of schooling 15.55 years, and literacy rate 95.52%. For the health dimension, life expectancy at birth was relatively stable, with a mean of 74.95 years and a standard deviation of 0.61, whereas stunting prevalence showed wider variation, ranging from 4.29% to 23.50%. These patterns indicate meaningful variation in poverty, education, and nutritional conditions across DI Yogyakarta, providing a suitable basis for the subsequent spatial-panel analysis.

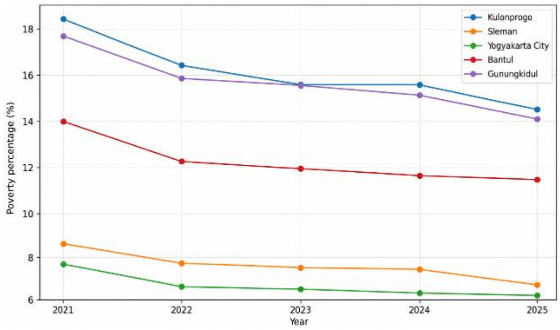

Figure 1. Trend of Poverty Percentage in DI Yogyakarta

Figure 1 shows a declining poverty trend across all regencies and the city of DI Yogyakarta during 2021–2025. Kulon Progo and Gunungkidul consistently recorded the highest poverty rates, while Sleman and Yogyakarta City remained the lowest. Although poverty declined in all regions, the pattern indicates that regional disparities persisted throughout the observation period.

To provide a cross-sectional view of regional disparities, Figure 2 presents the spatial distribution of poverty rates across the five regencies and city of the DI Yogyakarta in 2025.

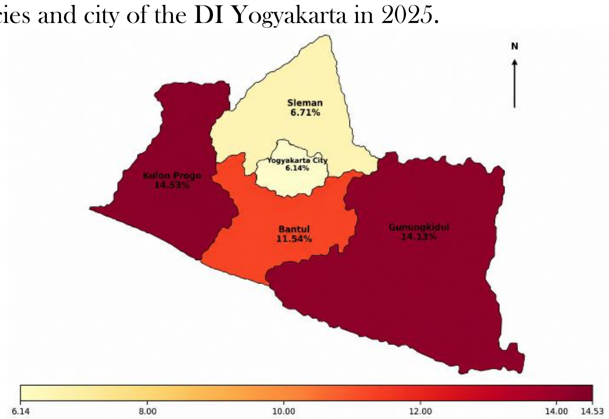

Figure 2. Choropleth Map of Poverty Rates by Regency/City in DI Yogyakarta, 2025

Figure 2 illustrates the spatial distribution of poverty rates in 2025. Higher poverty rates were concentrated in Kulon Progo and Gunungkidul, whereas lower rates were observed in Sleman and Yogyakarta City. This spatial pattern supports the need to examine whether poverty conditions are associated across neighbouring regions through spatial-panel analysis.

3.2. Panel Data Regression

3.2.1 Testing the specifications of a panel regression model

A sequence of panel model-selection tests and spatial dependence diagnostics was conducted to determine the appropriate model specification. As shown in Table 4, the Panel F test rejected the common-effects specification (p = 0.003), indicating that fixed regional effects should be considered. The Hausman test also rejected the random-effects specification (p = 0.009), supporting the use of the fixed-effects model. Although the Breusch–Pagan LM test did not support the random-effects model over the common-effects model (p = 0.823), the fixed-effects specification was retained as the preferred nonspatial panel model based on the Panel F and Hausman test results.

Spatial dependence was then evaluated using the within-transformed fixed-effects specification. The LM-lag test was statistically significant (p = 0.005), whereas the LM-error test was not significant (p = 0.457). This result supports a spatial lag specification rather than a spatial error specification. Therefore, the Spatial Autoregressive Fixed Effects Model (SARFEM) was selected as the main spatial-panel model. Given the small panel size (N=25, T=5), these tests are interpreted as exploratory model-selection evidence rather than definitive confirmation of the underlying spatial process.

Table 4. Panel Model Selection and Spatial Dependence Tests

Stage	Test	Null hypothesis	Test statistic	p-value	Decision
Nonspatial panel selection	Panel F (Chow) test	Common effects are adequate; no individual fixed effects	6.915	0.003	Reject H_0; FEM preferred to CEM
Nonspatial panel selection	Hausman test	REM estimates are consistent	16.967	0.009	Reject H_0; FEM preferred to REM
Nonspatial panel selection	Breusch–Pagan LM test	No random individual effect	0.050	0.823	Fail to reject H_0; REM not preferred to CEM
Spatial specification	LM-lag test on within model	$\rho = 0$; no spatial lag dependence	7.867	0.005	Reject H_0; spatial lag supported
Spatial specification	LM-error test on within model	$\lambda = 0$; no spatial error dependence	0.553	0.457	Fail to reject H_0; spatial error not supported

Note: The spatial LM tests were applied to the within-transformed fixed-effects specification using a row-standardized Queen contiguity matrix. Given N=5 and T=5, the p-values are interpreted as exploratory.

3.2.2 Panel regression model

Based on the model-selection tests, the Fixed Effects Model (FEM) was used as the nonspatial baseline because it allows region-specific intercepts to capture unobserved time-invariant heterogeneity that may be correlated with the education and health indicators. The FEM equation is specified as follows:

$$Poverty_{it} = \alpha_i - 2.123RLS_{it} - 4.446HLS_{it} - 0.379AMH_{it} + 0.197UHH_{it} - 0.022Stunting_{it}$$

The intercept value is then displayed in Table 5.

Table 5. Estimation of intercept values from each district/city in DI Yogyakarta

Parameter	Kulon Progo	Bantul	Gunungkidul	Sleman	Yogyakarta City
α_i	121.510	124.356	110.181	128.299	133.670

Table 5 indicates that the estimated intercepts differ across the five administrative areas, suggesting persistent regional heterogeneity. However, because the FEM does not account for spatial dependence among neighbouring regions, spatial diagnostic tests were conducted before estimating the final spatial-panel model.

3.3. Spatial panel regression analysis

3.3.1 Spatial Weighting Matrix

The spatial-panel analysis used a row-standardized first-order Queen contiguity matrix. Under this specification, two regions were considered neighbours when their administrative boundaries shared at least one point. The spatial units were ordered as Kulon Progo, Bantul, Gunungkidul, Sleman, and Yogyakarta City. Row standardization ensures that the nonzero weights in each row sum to one, allowing the spatially lagged poverty variable to represent the average poverty condition in neighbouring regions. The resulting matrix is presented in Table 6.

Table 6. Row-Standardized Queen Spatial Weights Matrix

Region	Kulon Progo	Bantul	Gunungkidul	Sleman	Yogyakarta City	Row Sum
Kulon Progo	0.000	0.500	0.000	0.500	0.000	1.000
Bantul	0.250	0.000	0.250	0.250	0.250	1.000
Gunungkidul	0.000	0.500	0.000	0.500	0.000	1.000
Sleman	0.250	0.250	0.250	0.000	0.250	1.000
Yogyakarta City	0.000	0.500	0.000	0.500	0.000	1.000

Table 6 shows that all row sums equal one, indicating that no region is isolated in the spatial structure.

3.3.2 Lagrange Multiplier Spatial Panel Test

After the fixed-effects model was selected as the preferred nonspatial specification, spatial dependence was evaluated using LM-lag and LM-error diagnostics on the within-transformed fixed-effects model. As reported in Table 4, the LM-lag test was significant ($p = 0.005$), whereas the LM-error test was not significant ($p = 0.457$). This result indicates that spatial dependence is better represented through a spatially lagged dependent variable than through spatially correlated errors. Therefore, the Spatial Autoregressive Fixed Effects Model (SARFEM) was selected as the main spatial-panel model. Given the small number of spatial units, this diagnostic evidence is interpreted cautiously as exploratory model-selection evidence.

$$\widehat{Poverty}_{it} = 0.629\sum_{j=1}^{N} w_{ij}\, Poverty_{jt} + \alpha_i - 0.347RLS_{it} - 2.965HLS_{it} - 0.229AMH_{it} + 0.135UHH_{it} - 0.024Stunting_{it}$$

3.3.3 Significance Test

The joint significance of the final SARFEM was evaluated using a Wald test. The test produced a statistic of 199.172 with 6 degrees of freedom and a p-value below 0.001, indicating that the spatial lag term and the education-health indicators were jointly associated with poverty rates in DI Yogyakarta. Given the small panel size, this result is interpreted as exploratory model-based evidence rather than definitive finite-sample inference.

Table 7 presents the individual parameter estimates of the SARFEM. The spatial lag coefficient was positive and statistically significant ($\rho = 0.629$, $p < 0.001$), indicating that poverty rates in one region were positively associated with poverty conditions in neighbouring regions. Among the explanatory variables, expected years of schooling had a negative and statistically significant coefficient ($\beta = -2.965$, $p < 0.001$), while mean years of schooling, literacy rate, life expectancy at birth, and stunting prevalence were not statistically significant. However, because the SAR model includes a spatially lagged dependent variable, substantive interpretation is based on the direct, indirect, and total effects reported in Table 8 rather than on the raw coefficients alone.

Table 7. SARFEM Estimation Results

Parameter	Coefficient	Std. Error	t-stat	p-value	Significance
Spatial lag (ρ)	0.629	0.119	5.272	0.000	Significant
RLS	-0.347	0.777	-0.447	0.655	Not Significant
HLS	-2.965	0.756	-3.924	0.000	Significant
AMH	-0.229	0.170	-1.347	0.178	Not significant
UHH	0.135	0.321	0.420	0.675	Not Significant
Stunting	-0.024	0.025	-0.985	0.325	Not Significant

3.3.4 Spatial Impact Decomposition

Table 8. Direct, Indirect, and Total Effects from the SARFEM

Variable	Coefficient	Direct effect	Indirect effect	Total effect
RLS	-0.347	-0.433	-0.502	-0.935
HLS	-2.965	-3.700	-4.292	-7.992
AMH	-0.229	-0.286	-0.332	-0.617
UHH	0.135	0.168	0.195	0.364
Stunting	-0.024	-0.030	-0.035	-0.065

Note: Direct, indirect, and total effects were calculated using the partial-derivatives approach based on the row-standardized Queen contiguity matrix and the estimated spatial lag coefficient (ρ=0.629). The values are interpreted as exploratory marginal associations due to the small panel size.

Table 8 presents the spatial impact decomposition from the SARFEM. Expected years of schooling showed negative direct, indirect, and total effects on poverty, indicating that higher expected years of schooling was associated with lower poverty both within the same region and in neighbouring regions through the spatial feedback structure of the SAR model. Mean years of schooling, literacy rate, and stunting prevalence also showed negative but smaller effects, while life expectancy at birth showed a positive effect and was not statistically significant in the baseline SARFEM. Given the small panel size, these results are interpreted as exploratory, context-specific associations rather than causal effects.

3.3.5 Sensitivity Analysis Using Alternative Spatial Weights

To evaluate whether the SARFEM estimates were sensitive to the choice of spatial weights matrix, the model was re-estimated using three weighting schemes: Queen contiguity, Rook contiguity, and inverse-distance weights. The same dependent variable, explanatory variables, individual fixed effects, observation period, and estimator were retained across all specifications. Thus, only the spatial weights matrix was changed. The results are presented in Table 9.

Table 9. Sensitivity of SARFEM Estimates to Alternative Spatial Weights

Variable	Queen contiguity	Std. Error	Rook contiguity	Std. Error	Inverse-distance	Std. Error
Spatial lag (ρ)	0.629	0.119	0.598	0.122	0.637	0.119
RLS	-0.347	0.777	-0.859	0.759	-0.501	0.765
HLS	-2.965	0.756	-2.379	0.830	-3.005	0.754
AMH	-0.229	0.170	-0.205	0.175	-0.194	0.172
UHH	0.135	0.321	0.166	0.327	0.236	0.322
Stunting	-0.024	0.025	-0.011	0.025	-0.013	0.025
Number of observations	25		25		25	

Overall, the alternative spatial weights produced directionally consistent results, especially for the spatial lag coefficient and expected years of schooling. Therefore, the baseline Queen-contiguity results can be considered qualitatively robust in terms of coefficient direction, although the small number of spatial units prevents strong claims about model stability.

3.3.6 Sensitivity Analysis Using One-Year-Lagged Regressors

Table 10. Sensitivity of SARFEM Estimates Using One-Year-Lagged Regressors

Variable	SARFEM	Std. Error	Lagged-regressor SARFEM	Std. Error
Spatial lag (ρ)	0.629	0.119	0.388	0.267
RLS	-0.347	0.777	-0.652	0.646
HLS	-2.965	0.756	-1.557	0.710
AMH	-0.229	0.170	-0.270	0.129
UHH	0.135	0.321	0.039	0.293
Stunting	-0.024	0.025	0.022	0.021
Number of observations	25		20	

The lagged-regressor robustness check supports the directional stability of the expected-years-of-schooling coefficient, but it also shows that the spatial lag effect becomes less precise when the sample is reduced to 20 observations. Therefore, the baseline findings are interpreted as conditional associations rather than causal effects.

3.3.7 Goodness-of-Fit Assessment

The goodness-of-fit assessment of the final SARFEM produced an in-sample (R-squared) of 0.993, indicating that the fitted values closely reproduced the observed variation in the 25 region-year observations. However, this high value should be interpreted cautiously. Because the model includes region-specific fixed effects and a spatially lagged dependent variable, a high in-sample fit may partly reflect the ability of the specification to capture regional heterogeneity and spatial dependence within the observed sample. Therefore, the R-squared value is not interpreted as evidence of equivalent predictive performance outside the 2021–2025 period or as confirmation of causal relationships. Model adequacy was assessed together with the Wald test, individual parameter estimates, spatial specification tests, residual diagnostics, and robustness checks using alternative model specifications.

3.3.8 Residual Diagnostics and Multicollinearity Assessment

Residual diagnostics and multicollinearity assessment were conducted to evaluate the adequacy of the final SARFEM. As shown in Table 11, the Jarque-Bera test did not indicate strong evidence of residual non-normality ($p = 0.606$), and the Breusch-Pagan test did not indicate statistically significant heteroscedasticity ($p = 0.224$). Moran's I on the model residuals was also not statistically significant ($p = 0.300$), suggesting no remaining spatial autocorrelation after the spatial lag structure was included. The VIF values were all below the conventional threshold of 10, with the highest value observed for life expectancy at birth (VIF = 4.301), indicating that severe multicollinearity was not detected. Given the small panel size, these diagnostics are interpreted as supporting evidence rather than definitive validation of the model.

Table 11. Residual Diagnostics and Multicollinearity Assessment

Diagnostic aspect	Test / indicator	Statistic / value	p-value	Interpretation
Normality	Jarque-Bera	1.001	0.606	No strong evidence of non-normality
Homoscedasticity	Breusch-Pagan	8.205	0.224	No statistically significant heteroscedasticity
Residual spatial autocorrelation	Moran's I	-0.377	0.300	No statistically significant residual spatial autocorrelation
Multicollinearity	Maximum VIF	4.301	-	Severe multicollinearity not detected

Note: The maximum VIF was observed for life expectancy at birth. All VIF values were below 10.

4. CONCLUSION

This study examined the associations of education and health indicators with poverty rates across the five regencies and city of DI Yogyakarta during 2021–2025 while accounting for regional fixed effects and spatial dependence. Descriptively, the average poverty rate declined from 13.28% in 2021 to 10.61% in 2025, although substantial differences remained across regions.

The Spatial Autoregressive Fixed Effects Model (SARFEM) indicated a positive spatial lag coefficient, showing that poverty rates in one region were associated with poverty conditions in neighbouring regions. Because the SAR specification includes a spatially lagged dependent variable, the interpretation of the explanatory variables was based on the direct, indirect, and total effects rather than on the raw coefficients alone. The spatial impact decomposition showed that expected years of schooling had negative direct, indirect, and total effects on poverty. This finding indicates that higher expected years of schooling was associated not only with lower poverty in the same region, but also with lower poverty in neighbouring regions through the spatial feedback structure of the model.

In contrast, the effects of mean years of schooling, literacy rate, life expectancy at birth, and stunting prevalence were weaker within the observed sample and period. These results should not be interpreted as evidence that these factors are unimportant, but rather that their independent associations with poverty were not strongly detected in this short panel after accounting for regional fixed effects and spatial dependence.

From a policy perspective, the findings suggest that poverty reduction initiatives in DI Yogyakarta may benefit from coordination across neighbouring regencies and the city rather than being designed solely within individual administrative boundaries. The negative direct and indirect effects of expected years of schooling also support continued attention to school participation, educational continuity, and access to learning opportunities, particularly in areas with persistently higher poverty rates. These recommendations are presented as policy considerations derived from associative evidence, not as causal claims.

Several limitations should be emphasized. The analysis is based on only 25 region-year observations, consisting of five spatial units observed over five years. Therefore, the model-based asymptotic standard errors, p-values, high in-sample model fit, and spatial impact estimates should be interpreted cautiously. The findings are exploratory and specific to DI Yogyakarta during 2021–2025; they should not be treated as evidence of out-of-sample predictive accuracy or causal effects. In addition, although fixed effects and robustness checks help reduce some concerns, they do not fully eliminate reverse causality or omitted time-varying confounding. Future research should use longer panels, additional socioeconomic controls such as employment structure, income, fiscal capacity, infrastructure, and social protection, alternative spatial weights, finite-sample inference procedures, and full spatial impact analysis to assess the stability of these relationships.

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