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The Role of Human Capital Based on Education and Health against poverty in 34 provinces in Indonesia

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Abstract: This study aims to analyse the influence of human capital, as measured by education and health, on poverty levels in 34 provinces in Indonesia. Using quantitative methods with panel data for the 2020–2024 period, this study applies a fixed effect model based on the results of the Chow and Hausman tests. Testing is carried out through panel regression, t-tests, F-tests, and classical assumption testing to ensure model validity. The results of the study show that education has a negative and significant effect on poverty, which means that increasing the average length of schooling can reduce the number of poor people. In contrast, health as measured by life expectancy has a positive and significant effect, indicating structural variations between regions that require further study. Simultaneously, both human capital variables have a significant influence on poverty. A limitation of this study is that the capability indicators used are limited to education and health, thus not reflecting the full dimensions of the capability approach. Therefore, future researchers are advised to include other variables such as access to technology, employment opportunities, environmental conditions, or social protection to provide a more comprehensive picture of the determinants of poverty in Indonesia.

Keywords: Human Capital, Education, Health, Poverty, Capability Approach.

INTRODUCTION

Poverty in Indonesia is a multidimensional issue shaped not only by low income but also by limited access to education and health services, which constitute essential human capabilities. The *capability approach* views poverty as a deprivation of fundamental abilities required to lead a meaningful life (Sen, 1999), while human capital theory emphasises education and health as long-term investments that enhance productivity and economic opportunities (Becker, 1964; Schultz, 1961). International studies consistently show that improvements in human capital significantly reduce poverty (Comfort et al., 2019; Yun-li et al., 2021). In Indonesia, persistent disparities in education and health across regions indicate that these capabilities have not been fully realized in reducing socioeconomic vulnerability (World Bank, 2016).

Existing studies in Indonesia highlight the strong role of education in improving household welfare. Education has been shown to enhance social mobility (Haidir & Setyari, 2024) and significantly improve household economic status, particularly at the secondary and tertiary levels (Arsani et al., 2020). The education index also demonstrates a negative relationship with poverty across provinces (Said et al., 2025). However, most of these studies assess education separately from health, leaving a limited understanding of how these two components of human capital jointly shape poverty outcomes.

Evidence on the role of health in poverty reduction reveals greater variability. Improved life expectancy and better health services can reduce poverty (Basworo & Atmanti, 2024; Qudsi & Ashar, 2025), yet several provinces with relatively high health indicators continue to experience substantial poverty. This pattern suggests that structural factors such as income inequality, population density, urbanization, and regional economic composition may weaken or distort the expected relationship between health improvements and poverty reduction.

These conditions indicate the need for a study that examines education and health simultaneously in explaining poverty variations across Indonesian provinces. Prior research in Indonesia has generally analysed these two components of human capital separately, leaving the joint and interactive influence of education and health largely unexplored. This study addresses this limitation by integrating both indicators into a single analytical framework and by examining how their effects vary across provinces with differing structural characteristics. In addition, the study provides new insight by offering a critical explanation for empirical results that deviate from theoretical expectations—such as provinces with high life expectancy but persistent poverty—through the lens of regional inequality, demographic pressure, and economic structure. Through this approach, the study contributes a more comprehensive and context-sensitive understanding of poverty dynamics in Indonesia, representing a substantive advancement beyond previous studies that have treated human capital dimensions in isolation.

METHOD

This study employs a panel data approach using provincial observations from 2020–2024, with the Fixed Effects Model (FEM) selected based on both statistical and theoretical considerations. The Chow test rejects the pooled model, and the Hausman test confirms that provincial unobserved characteristics correlate with the regressors, making FEM the consistent estimator while rendering the Random Effects and LM tests unnecessary. The FE structure is theoretically appropriate because provinces differ in structural, institutional, and geographic characteristics that remain constant over time yet plausibly influence education, health, and poverty simultaneously; the FE estimator absorbs these unobserved factors and focuses on within-province changes, which aligns with the study's objective of examining human capital dynamics over time.

Diagnostic testing indicates the presence of autocorrelation; therefore, a GLS estimator is additionally reported as a corrective approach to improve efficiency, while FEM remains the baseline model for interpretation. Education and health serve as the main explanatory variables representing the core dimensions of human capital, with average years of schooling and life expectancy capturing long-term productivity and well-being. The mathematical model equation is:

$$Yit = \beta 0 + \beta 1\ X1\ it + \beta 2\ X2\ it + \varepsilon$$

Where to represent (Yit) poverty level at entity i and time t, β 0 is a constant. β1 and β2 each is the regression coefficient for the independent variable of education level ($X1it$) , education level k health ($X2it$). Meanwhile, Ɛ represents the error term that reflects the influence of other factors outside the model.

This study aims to analyse the factors influencing poverty levels in Indonesia using inter-provincial data for the 2020–2024 period. The primary focus of this study is on education and health variables, which play a crucial role in improving the quality of human resources and potentially reducing poverty. The data used are secondary data sourced from the Central Statistics Agency (BPS). Each variable in this study is operationally defined based on development economics and welfare theories, such as human capital theory and the concept of multidimensional poverty, to accurately reflect the actual conditions of communities in Indonesia's 34 provinces. The operational definitions, indicators, and data sources for each variable are detailed in the following table.

After the most appropriate panel data model has been determined through model specification testing, the next step is hypothesis testing. This testing aims to determine the effect of the independent variables on the dependent variable in the research model. The hypothesis testing methods used include the coefficient of determination (R^2), partial tests (t-test), and simultaneous tests (F-test).

The coefficient of determination (R^2) test is used to measure how much of the proportion of variation in the dependent variable (poverty) can be explained by the independent variables used in the model, namely the level of education and health. The R^2 value that is getting closer to 1 indicates that the model has better ability to explain the variation in the dependent variable. The R^2 value that is increasingly far from 1 indicates that the model has an increasingly poor ability to explain the variation in the dependent variable.

The t-test (partial test) is used to test the significance of the influence of each independent variable on the dependent variable individually. This test aims to determine whether the education (X_1) and health (X_2) variables have a significant influence on the poverty level (Y) at a certain significance level ($\alpha = 0.05$) . If the probability value (p-value) < 0.05 , then the alternative hypothesis (Ha) is accepted, which means the independent variable has a significant effect on the dependent variable. If the probability value (p-value) < 0.05, then the alternative hypothesis (Ha) is accepted, which means the independent variable has a significant effect on the dependent variable. If the probability value (p-value) > 0.05, then the alternative hypothesis (H_1) is rejected, which means the independent variable does not affect the dependent variable.

The F test (simultaneous test) is used to test whether all independent variables in the model simultaneously have a significant effect on the dependent variable. This F test aims to ensure that the model used is fit to explain the relationship between variables in the study. The probability value (p-value) of the F test < 0.05, then it can be concluded that the education and health variables simultaneously have a significant effect on the poverty rate in Indonesia. The probability value (p-value) of the F test > 0.05, so it can be concluded that the education and health variables simultaneously do not have a significant effect on the poverty rate in Indonesia.

In addition to hypothesis testing, this study also conducted classical assumption tests to ensure that the regression model met *the Best Linear Unbiased Estimator* (BLUE) criteria. The classical assumption tests performed included tests for normality, multicollinearity, heteroscedasticity, and autocorrelation. The normality test aims to determine whether the residual data is normally distributed. The multicollinearity test is used to detect the presence of high correlation between independent variables, which can affect the stability of the regression coefficient. The heteroscedasticity test is carried out to determine whether there is inequality in the residual variance in each observation, while the autocorrelation test aims to detect a relationship between the residuals in one period and the residuals in the previous period. If the model meets these four assumptions, the estimation results can be said to be valid and reliable.

RESULTS AND DISCUSSION

Panel Data Model Selection

Chow Test

The Chow test is used to determine whether the pooled OLS model can be maintained or whether a Fixed Effects model is more appropriate. Table 2 shows that the probability value of the cross-section F statistic is 0.0000, well below the 0.05 significance level. This result indicates that the pooled model is rejected, and the Fixed Effects specification is preferred. Therefore, the model must include provincial-specific effects.

Table 1. Chow Test

Redundant Fixed Effects Tests
Equation: Untitled
Cross-section fixed effects test

Effects Test	Statistics	df	Prob.
Cross-section F	1298.552098	(33,133)	0.0000

Source: Eviews

This outcome requires the next step, evaluating whether the fixed effect estimator is also preferable to the random effects estimator using the hausman test.
Hausman test

The Hausman test assesses whether the Random Effects estimator is consistent by examining the correlation between individual effects and explanatory variables. The test result in Table 3 shows a probability value of 0.0363, which is below the 0.05 threshold. This indicates that the Random Effects estimator is inconsistent because unobserved provincial characteristics are correlated with the regressors.

Table 2. Hausman Test

Correlated Random Effects - Hausman Test
Equation: Untitled
Cross-section random effects test

Test Summary	Chi-Sq. Statistic	Chi-Sq. df	Prob.
Random cross-section	6.633451	2	0.0363

Source: Eviews

Since both the Chow test and Hausman test independently favor the Fixed Effects Model, the Random Effects Model is not used, and the Lagrange Multiplier (LM) test becomes unnecessary. Consequently, the Fixed Effects estimator is selected as the baseline model for the analysis.

Classical Assumption Test

Multicollinearity Test

One of the important assumptions in regression analysis is the absence of multicollinearity between independent variables. Multicollinearity occurs when two or more independent variables have a high correlation that can disrupt the stability and interpretation of the model. To ensure the suitability of the regression model, a multicollinearity test was performed using the correlation matrix between variables. The following table shows the correlation between variables X1 and X2.

Table 3. Multicollinearity Test

X1	X2
1	0.413079312734444
0.413079312734444	1

Source: Eviews

Based on the results of the multicollinearity test in table 4.4, it shows that the correlation value of the independent variables is less than 0.8, so it can be concluded that there is no multicollinearity problem.

Heteroscedasticity Test

Heteroscedasticity is a condition where the residual variance is not constant at each level of the independent variable. The presence of heteroscedasticity can cause inefficient coefficient estimation and biased standard errors, thus compromising the validity of statistical tests. Therefore, a heteroscedasticity test is performed to detect whether the model experiences inconsistencies in residual variance. The following table presents the results of the heteroscedasticity test.

Table 4. Heteroscedasticity Test

Dependent Variable: ABS(RESID)
Method: Panel Least Squares
Date: 11/16/25 Time: 21:15
Sample: 2020 2024
Periods included: 5
Cross-sections included: 34
Total panel (unbalanced) observations: 169

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	447.6379	610.0504	0.733772	0.4644
X1	20.47811	15.53021	1.318598	0.1896
X2	-8.703411	10.49709	-0.829126	0.4085

Source: Eviews

Based on the results of the heteroscedasticity test in Table 5, it shows that all independent variables have probability values greater than the *alpha value of* 0.05, so they are free from heteroscedasticity problems.

Autocorrelation Test

Table 5 reports the Durbin–Watson statistic of 0.008, which is far below the lower bound indicating no autocorrelation. This extremely low value confirms the presence of strong positive autocorrelation in the residuals of the Fixed Effects model. Autocorrelation is common in macro-panel data and, although it does not invalidate the Fixed Effects estimator, it affects the efficiency of the standard errors. Therefore, a correction method is required to produce more reliable estimates.

Table 5. Autocorrelation Test

Dependent Variable: Y
Method: Panel Least Squares
Date: 11/19/25 Time: 09:00
Sample: 2020 2024
Periods included: 5
Cross-sections included: 34
Total panel (unbalanced) observations: 169

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-9497.971	1984.433	-4.786238	0.0000
X1	-563.3783	85.23673	-6.609571	0.0000
X2	222.2811	31.71469	7.008774	0.0000

Root MSE	911.5714	R-squared	0.283258
Mean dependent var	764.0137	Adjusted R-squared	0.274622

SD dependent var	1079,936	SE of regression	919.7716
Akaike info criterion	16.50372	Sum squared residual	1.40E+08
Schwarz criterion	16.55928	Log likelihood	-1391,564
Hannan-Quinn criter.	16.52627	F-statistic	32.80172
Durbin-Watson stat	0.008124	Prob(F-statistic)	0.000000

Source: Eviews

Given the presence of autocorrelation, the model is re-estimated using the Generalized Least Squares (GLS) approach, which adjusts the error structure and improves efficiency under heteroskedasticity and serial correlation. Table 6 presents the results of the GLS estimation, showing an improved Durbin–Watson value of 1.78, which falls within the range indicating the absence of autocorrelation.

Table 6. Autocorrelation Test using GLS

Dependent Variable: Y
Method: Panel EGLS (Cross-section weights)
Date: 11/18/25 Time: 07:43
Sample: 2020 2024
Periods included: 5
Cross-sections included: 34
Total panel (unbalanced) observations: 169
Linear estimation after one-step weighting matrix

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	116.9760	453.9157	0.257704	0.7970
X1	-185.8417	21.36286	-8.699288	0.0000
X2	33.39660	8.852205	3.772687	0.0002

Effects Specification

Cross-section fixed (dummy variables)

Weighted Statistics

Root MSE	44.17777	R-squared	0.996945
Mean dependent var	1057,549	Adjusted R-squared	0.996141
SD dependent var	783.8775	SE of regression	49.79908
Sum squared residual	329833.1	F-statistic	1239,992
Durbin-Watson stat	1.788259	Prob(F-statistic)	0.000000

Source: Eviews

The results in Table 6 represent the baseline Fixed Effects (FE) model, selected through the Chow and Hausman tests and therefore serving as the primary estimator. However, the FE residuals exhibit positive autocorrelation, which necessitates correction. Table 6 provides the GLS-corrected estimation, which addresses autocorrelation and heteroskedasticity to produce more efficient standard errors. GLS is used exclusively as a correction method, not as a replacement for the FE model. Therefore, the FE model remains the baseline for substantive interpretation, while the GLS results serve as supporting evidence to strengthen the robustness of the findings.

Panel Data Regression Results

Based on the autocorrelation results by changing the regression into *Generalized Least Square* (GLS) regression, the regression results can be seen in this table.

Table 7. Panel Data Regression Test

Dependent Variable: Y?
Method: Pooled EGLS (Cross-section weights)
Date: 11/19/25 Time: 09:55
Sample: 1 5
Included observations: 5
Cross-sections included: 34
Total pool (unbalanced) observations: 169
Linear estimation after one-step weighting matrix

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	116.9760	453.9157	0.257704	0.7970
X1?	-185.8417	21.36286	-8.699288	0.0000
X2?	33.39660	8.852205	3.772687	0.0002
Fixed Effects (Cross)				
ACEH--C	175.9308			
BALI--C	-563.9335			
BANTEN--C	94.30739			
BENGKULU--C	-424.7524			
DIYOGYAKARTA--C	-291.1885			
DKI JAKARTA--C	81.08321			
GORONTALO--C	-666.1345			
JAMBI--C	-547.2507			
WEST JAVA--C	3092.540			
CENTRAL JAVA--C	2799.835			
EAST JAVA--C	3308.635			
WEST KALIMANTAN--C	-662.4689			
SOUTH KALIMANTAN--C	-598.8450			
CENTRAL KALIMANTAN--C	-637.4615			
EAST KALIMANTAN--C	-476.7948			
NORTH KALIMANTAN--C	-715.7882			
KEPBANGKABELITUNG--C	-838.0609			
KEPRIAU--C	-350.3269			
LAMPUNG--C	106.7118			
MALUKU--C	-86.00087			
NORTH MALUKU--C	-559.4775			
WEST NUSATENGARARAT--C	-153.5879			
EAST NUSATENGARATUMUR--C	278.7713			
PAPUA--C	-122.1272			
PAPUABARAT--C	-634.0249			
RIAU--C	-247.3548			
WEST SULAWESI--C	-587.9023			
SOUTH SULAWESI--C	-48.24433			
CENTRAL SULAWESI--C	-305.6855			
SOUTHEAST SULAWESI--C	-407.0750			
NORTH SULAWESI--C	-472.7949			
WEST SUMATRA--C	-312.1079			
SOUTH SUMATRA--C	211.4772			
NORTH SUMATRA--C	700.1220			

Effects Specification

Cross-section fixed (dummy variables)

Weighted Statistics			
Root MSE	44.17777	R-squared	0.996945
Mean dependent var	1057,549	Adjusted R-squared	0.996141
SD dependent var	783.8775	SE of regression	49.79908
Sum squared residual	329833.1	F-statistic	1239,992
Durbin-Watson stat	1.788259	Prob(F-statistic)	0.000000

Unweighted Statistics			
R-squared	0.997495	Mean dependent var	764.0137
Sum squared residual	490815.0	Durbin-Watson stat	1.605772

Source: Eviews

The regression equation contains constant values for each research variable. The explanation of each variable coefficient is as follows:

1. 116.9760 : If Education and Health are 0, then the average poverty rate is 116.9760 people
2. 185,8417: If there is an increase in the level of education (average length of schooling) by 1 year, then the average poverty rate will decrease by 185,8417 people.
3. 33.39660: If there is an increase in the health level (life expectancy) by 1 year, then the average poverty rate will increase by 33.39660 people.

A positive intercept indicates that, before taking into account the Education (X1) and Health (X2) variables, the following provinces have higher poverty rates than the model baseline. Provinces with positive intercepts include Aceh, Banten, DKI Jakarta, West Java, Central Java, East Java, Lampung, South Sumatra, North Sumatra, and East Nusa Tenggara. The largest intercept values are found in three provinces on Java Island: East Java (3308,635) , West Java (3092,540), and Central Java (2799,835) . This indicates that these three provinces have high baseline poverty levels before considering education and health factors, possibly influenced by their large populations or variations in poverty distribution across regions. Other provinces with positive intercepts, such as Aceh, North Sumatra, Lampung, and NTT, also show relatively higher baseline poverty levels compared to provinces with negative intercepts.

A negative intercept indicates that the province has a lower average initial poverty rate than the baseline, after the effects of education and health are not included in the model. Provinces with negative intercepts include Bali, Bengkulu, DI Yogyakarta, Gorontalo, Jambi, West Kalimantan, South Kalimantan, Central Kalimantan, East Kalimantan, North Kalimantan, Bangka Belitung Islands, Riau Islands, Maluku, North Maluku, West Nusa Tenggara, Papua, West Papua, Riau, West Sulawesi, South Sulawesi, Central Sulawesi, Southeast Sulawesi, North Sulawesi, and West Sumatra. The lowest intercept values are found in Bangka Belitung Islands (-838.0609), North Kalimantan (-715.7882), and Gorontalo (-666.1345), indicating that the baseline poverty rate in these provinces is lower than in other provinces in the model. Provinces in Eastern Indonesia such as Maluku, North Maluku, and Papua also show negative intercept values, which may indicate that the impact of poverty will only become larger when education or health variables are included.

Hypothesis Testing

t-test

The Significance Test (t-Test) is used to determine the level of significance of the influence of independent and dependent variables by assessing the *t-statistic* . This test explains the partial influence of education and health on poverty in Indonesia. Decision-making in this t-test is done by comparing the calculated t-value with the t-table, and the probability value is compared with the error rate determined by the researcher. The following table shows the results of the t-test.

Table 8. t-test

Variables	Coefficient	t-Statistic	t-Table	Prob.	Information
X1	-185.8417	-8.699288	1,974	0.0000	Significant
X2	33.39660	3.772687	1,974	0.0002	Significant

Source: Eviews

The education variable shows a negative and statistically significant coefficient, indicating that higher levels of educational attainment are associated with lower poverty levels. This finding aligns with theoretical expectations that education enhances productivity and expands economic opportunities. The health variable, proxied by life expectancy, also appears statistically significant but shows a positive coefficient. This result diverges from standard human capital theory, which predicts that improved health conditions should reduce poverty. The positive association should not be interpreted as a causal effect of health increasing poverty; rather, it likely reflects deeper structural characteristics across provinces. Regions with higher life expectancy may still experience persistent poverty due to inequality, economic structure, demographic pressures, or the possibility of endogeneity and reverse causality. Therefore, this finding must be interpreted with caution.

F test

Simultaneous hypothesis testing is a test carried out to determine how much influence the independent variables have when combined with the dependent variable. The results of the simultaneous hypothesis test can be seen in the following table.

Table 9. f test

F-statistic	1239,992
Prob(F-statistic)	0.000000

Source: Eviews

Based on the results of the F Statistic test, it is 1239.992 > 3.05 f table and the probability value of f statistic is 0.000000 < 0.05 so that the education and health variables simultaneously have an effect on poverty.

Coefficient of Determination Test

The overall R-squared value obtained from the Fixed Effects estimation is 0.9969, which appears extremely high at first glance. However, this figure cannot be interpreted to mean that nearly all variations in poverty are explained by education and health. In Fixed Effects (FE) models, the inclusion of provincial dummy variables absorbs most of the cross-sectional variation, often resulting in an inflated overall R^2. This pattern is common in FE regressions, especially when the number of cross-sectional units is relatively large (Baltagi, 2008; Wooldridge, 2010).

Table 10. Determination Coefficient Test

	Square Value
R- *Square*	0.996945

Source: Eviews

Such a high R^2 therefore reflects the ability of the FE intercepts to capture time-invariant structural differences across provinces, rather than the explanatory power of the independent variables themselves. A more relevant indicator in FE analysis is the within R^2, which measures how much of the variation over time within each province is explained by the regressors. Consequently, the extremely high R^2 should be viewed as a statistical artifact of the FE specification rather than evidence of an almost perfect model fit.

Discussion

The negative and significant effect of education on poverty is consistent with human capital theory, which states that increased schooling enhances skills, productivity, and long-term earning capacity (Becker, 1964; Schultz, 1961). Empirical conditions in Indonesia show that provinces with higher educational attainment tend to have lower poverty rates because their labor markets are more capable of absorbing skilled workers (Nugroho & Negara, 2020). Regions such as Jakarta, Bali, and Yogyakarta benefit from stronger economic diversification and higher-quality employment opportunities, making the role of education more effective in reducing poverty (Ginting & Aji, 2020).

The positive coefficient of life expectancy requires careful interpretation because it diverges from theoretical expectations that better health should reduce poverty. Provinces with high life expectancy often face structural challenges such as persistent inequality, aging populations, and dense urban labor markets that limit the poverty-reducing impact of improved health indicators (World Bank, 2016; Aiyar et al., 2016). Life expectancy in this context may reflect long-term demographic transitions rather than immediate welfare conditions, which creates the appearance of a positive association with poverty despite underlying socioeconomic stress (Jefry & Irhamah, 2018).

The structural differences between Java and non-Java regions play a significant role in shaping the estimated effects of education and health. Provinces outside Java frequently experience weaker infrastructure, limited access to quality public services, and narrower formal labor markets, reducing the effectiveness of human capital improvements in lowering poverty (Asian Development Bank, 2020). Java's provinces benefit from stronger institutional capacity and industrial concentration, which enables educational gains to translate more consistently into welfare improvements (Fields, 2011).

The high provincial intercepts found in the Fixed Effect model highlight the presence of deep-rooted characteristics that remain constant over time. These intercepts capture factors such as high cost of living, entrenched inequality, and urban economic structures that contribute to baseline poverty levels independently of education and health (Lewis, 1954; Yusuf et al., 2022). The prominence of Java's provinces in these intercepts reflects the coexistence of advanced economic development with significant internal disparities, which shapes the overall poverty dynamics in the region.

The findings reinforce that poverty in Indonesia is shaped by complex interactions between human capital, demographic pressures, and structural regional disparities. The simultaneous analysis of education and health provides a more comprehensive view of poverty determinants compared to studies that examine these variables separately. The results also show that deviations from theoretical expectations, particularly in the case of life expectancy, are better understood through Indonesia's unique demographic and socioeconomic conditions, thereby offering a more nuanced explanation of poverty patterns across provinces.

CONCLUSION

The study finds that education exerts a negative influence on poverty, indicating that greater educational attainment contributes to lower poverty levels across Indonesian provinces. This result strengthens the theoretical foundations of human capital and the capability approach, both of which emphasize that improvements in skills, knowledge, and cognitive capacity expand individuals' real opportunities and long-term economic prospects. Health, represented through life expectancy, exerts a positive influence on poverty, a finding that departs from conventional theory. This outcome provides a theoretical contribution by demonstrating that health indicators may capture underlying structural pressures, demographic transitions, or income inequality rather than directly reflecting household welfare conditions.

The findings generate several policy implications that are relevant for addressing structural poverty in Indonesia. Strengthening educational quality, improving teacher distribution, and expanding vocational and technical training programs are essential steps to enhance human capital formation. Enhancing health outcomes requires policies aimed at reducing interprovincial disparities in health infrastructure, addressing stunting, and expanding community-based health services, especially in regions experiencing demographic pressures or persistent inequality. These policy efforts should be integrated with broader strategies linking education, health, technology access, and social protection, consistent with the capability approach's emphasis on expanding individuals' substantive freedoms.

The study has several limitations that must be acknowledged. The measurement of capability is limited to education and health, which does not fully represent the multidimensional nature of Sen's broader capability framework. The fixed-effect model cannot completely address potential endogeneity or omitted variable bias that may influence both human capital and poverty. The availability of provincial panel data restricts the inclusion of additional structural indicators such as job quality, digital access, or environmental vulnerability.

Future research is encouraged to incorporate a wider range of capability dimensions and to use more advanced econometric methods. Expanding the analysis to include employment quality, digital inequality, environmental conditions, and spatial dynamics would enhance understanding of the mechanisms through which capabilities influence poverty. Applying dynamic panel models, spatial econometric approaches, or household-level datasets may provide deeper insights into how education and health interact with structural disparities to shape poverty outcomes across Indonesia.

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