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The Impact of Human Development Quality on Poverty: Evidence from Panel Data of South Sulawesi Province

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Abstract

The eradication of poverty is a critical priority for both central and local governments. Human development plays a vital role in lifting communities out of poverty. This study examines how the quality of human development affects poverty across 24 districts/cities of South Sulawesi over 2012–2022, using the Generalized Method of Moments (GMM). Life expectancy, as a proxy for health quality, has no significant effect on poverty reduction, whereas primary and secondary school enrolment rates show a significant negative effect. Government spending on education and health also reduces poverty significantly, while the open unemployment rate and the COVID-19 dummy are associated with higher poverty. Per capita expenditure and access to clean water show no significant effect. The study contributes district-level evidence on poverty, using a dynamic panel approach that accounts for the persistence of poverty over time and corrects for endogeneity. ***Its originality lies in*** *addressing the gap between the province's rising human development index and a poverty level that has not declined alongside it, which gives local government a more targeted basis for policy.*

Keywords: Human Development, Poverty, Health, Education, and GMM

JEL Classifications: C01 and O15

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Introduction

Poverty reduction is the first of the 17 Sustainable Development Goals (SDGs) adopted by 193 member states, including Indonesia. It is tied to the goals of good health (SDG 3) and quality education (SDG 4), the two dimensions on which human development is built; thus, progress on poverty cannot be separated from progress on the health and schooling of a population. Indonesia has carried this commitment into national policy, with the National Medium-Term Development Plan (RPJMN) 2020–2024 placing poverty reduction among its main development priorities.

Poverty is shaped by interrelated factors such as education, health, income, access to basic services, geographical location, and the environment, which tend to reinforce one another rather than act in isolation. Low human development quality in managing natural resources can also lead to poverty (Fadila & Marwan, 2020). When a population is poorly educated and in vulnerable health, people remain unskilled and have little knowledge to manage the resources available to them, which hinders economic activity and sustains poverty in a region (Syaifullah & Nazaruddin, 2017).

The issue of poverty at the regional level is serious, as its impact tends to widen and reach many aspects of life (Priseptian & Wiwin, 2022). The concern is not only the depth of poverty in any one year but also its tendency to carry over into the next, which makes regions that are already behind the hardest to lift. Data from the BPS (2023) recorded an increase of 12.19 thousand in the number of poor people on Sulawesi Island. Among the six provinces in Sulawesi, South Sulawesi contributed the most, adding 6.59 thousand poor residents, which is more than half of the island's total rise. As this number grew, the provincial poverty rate in 2023 also increased, even as the national rate fell by 0.21 percent. Thus, the province moved against the national trend in the very year that the country as a whole was making progress.

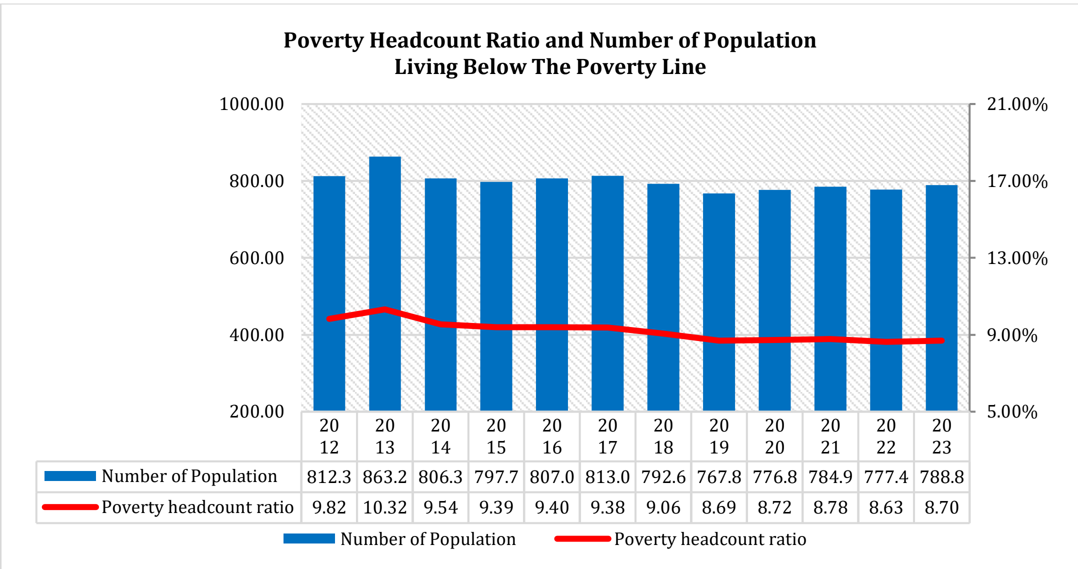

Figure 1. Poverty Headcount Ratio and Number of Population Living Below the Poverty Line (BPS, 2024)

According to data from the BPS South Sulawesi (2024a), the provincial poverty rate averaged approximately 8.70 percent between 2012 and 2023. The rate is volatile, remaining relatively high without a clear downward shift. The number of people living below the poverty line followed the same pattern. The largest rise occurred from 2012 to 2013, from 812.30 to 863.20 thousand, and since then, the figure has fluctuated within the 770–800 thousand range, a slight decline that still leaves it at a high level. The burden is uneven across provinces. The poor are concentrated in a few regencies, with Bone, Makassar, and Gowa recording the largest poor populations and Palopo, Barru, and Parepare recording the smallest. This mix of a high, persistent provincial rate and sharp gaps between regencies is what a single provincial figure conceals, and it is why the analysis is taken to the district level.

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This study aims to analyze how the quality of human development affects poverty across the 24 districts/cities of South Sulawesi over 2012–2022. Most Indonesian studies on the relationship between HDI and poverty use static panel estimators at the provincial or national level (Syaifullah & Nazaruddin, 2017; Prasetyoningrum & Sulia, 2018). However, poverty today partly depends on poverty yesterday, and when government spending responds to poverty as much as it drives down, those models produce biased estimates. Its novelty is twofold. It addresses a specific empirical puzzle, where Data from BPS (2024b) show that the number of poor people fluctuated while the Human Development Index (HDI) steadily increased. It also moves the analysis to the district level, where most prior work on this relationship stops at the provincial or national scale, and applies a dynamic panel approach that accounts for the persistence of poverty and corrects for endogeneity (Cammerat, 2020; Xie et al., 2023; Spada et al., 2024).

Literature Study

Increasing human resource capacity is one of the efforts of the South Sulawesi government to address the issue of poverty, as stated in the South Sulawesi Province RPJMD document for 2018-2023 Mission 5, "Realizing Competitive, Inclusive, and Characterized Human Quality." According to Gruzina et al. (2021), improving the quality of human resources plays an important role because the progress of a region is determined not only by the size of the GRDP but also by the quality of health and education of the people in it. Improving the quality of education and public health is a crucial step in addressing poverty (Sabir & Aziz, 2018).

Ali and Ahmad (2013) show that improving the quality of education and health sectors affects poverty through the HDI. According to Sen (1999), poverty is not just about low income but also a lack of basic capabilities. This perspective emphasizes the substantive freedom to lead a life that one has reason to value, including the opportunity to access decent healthcare and proper education. Therefore, development must be evaluated by the expansion of such human capabilities, not merely economic growth. However, based on data from the BPS South Sulawesi (2024b), the HDI value of South Sulawesi Province has continuously increased and entered the high HDI category (>70) since 2017. Despite this, the increase in HDI has not been followed by a decrease in the population living below the poverty line. In contrast, the number of people living below the poverty line from year to year shows a fluctuating and increasing trend.

The relationship between human development and poverty is based on human capital theory. Becker (1994) conceptualizes expenditures on education, training, and medical care as investments in human capital that generate returns comparable to those from physical capital investments. The underlying mechanism operates through productivity: education enhances workers' skills, while good health preserves their capacity to work, both of which lead to higher earnings and consequently reduce the risk of poverty. Similarly, Eide and Showalter (2010) adopt an individual-level perspective, wherein a person invests in health and education with the expectation of achieving greater future income. Sen (1999) capability approach treats poverty as a deprivation of the capabilities people need to live the kind of life they have reason to value, which reaches beyond what they earn or spend.

This contradicts the findings of Spada et al. (2024). Wani and Dhami (2021) and Wu et al. (2024) show that improving the quality of health and education status improves the quality of life of the community, thereby lifting them out of poverty. Similar findings by Marsinta et al. (2020) in their research state that improving the quality of health and education can be a solution to address the problem of poverty in the region. Abdulrahman (2022) also found a long-term impact of improving human capital quality on reducing the number of poor people. Individuals invest in health and education with the expectation that these investments will provide benefits in the form of higher income (Tsaurai K., 2022). In a case study in Indonesia, Sofilda et al. (2013) found a significant negative impact of improving human development quality and reducing poverty in Papua Province.

The trend of increasing HDI that is not followed by a decrease in the population living below the poverty line in South Sulawesi Province indicates a gap between the previous research findings and empirical conditions. Various studies have proven that the poverty of a region is influenced by the quality of human resources. Therefore, further research is needed to analyse the impact of human development quality on poverty at the district/city level in South Sulawesi Province. The benefits of this research include providing empirical evidence of the dynamic panel data model in the district/city context and offering the government to develop effective policies against poverty.

Research Methodology

This study employs secondary data on 24 regencies in South Sulawesi Province from 2012 to 2022. This study uses dynamic panel data regression with the Generalized Method of Moments (GMM) to address endogeneity issues and provide robust estimates. The use of GMM follows from how poverty is modelled, as three features make the regressors endogenous. First, the lagged dependent variable ($lnPov_{it}$) is correlated with the regency-specific error term because the unobserved conditions that keep a regency poor persist over time. Static fixed effects and OLS cannot remove this correlation; therefore, lagged levels serve as instruments (Arellano & Bond, 1991; Blundell & Bond, 1998). Second, fiscal and economic controls are subject to reverse causality: per capita expenditure and government spending on education and health are shaped by poverty as much as they shape it. Third, human development and poverty are jointly determined; using Indonesian data, Sofilda et al. (2013) confirm a two-way relationship in a simultaneous-equations model, where poverty erodes health and schooling, while weak health and schooling keep households poor.

The assumption is that poverty tends to persist into the future and that current values may be explained by past values. This assumption aligns with the studies by Cammeraat (2020), Xie et al. (2023), and Spada et al. (2024), which use lagged dependent variables to address endogeneity issues and accommodate the dynamic nature of poverty trends.

The approaches used in estimating dynamic panel data models are First-Difference GMM (FD-GMM) and System GMM (SYS-GMM). The FD GMM was developed by Arellano and Bond (1991), and this method transforms the data to eliminate fixed effects and uses lagged levels of the variables as instruments.

$$\Delta Y_{it} = \alpha \Delta Y_{it-1} + \beta \Delta X_{it} + \beta_3 + \Delta e_{it} \quad (1)$$

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In this model, ΔY_{it} represents the first difference of the dependent variable (poverty indicator) in regency *i* at time t, and ΔY_{it-1} is the lagged first difference of the dependent variable to capture the dynamic nature of poverty. ΔX_{it} is a matrix of independent variables consisting of the variable of interest and control variables as instruments to address potential endogeneity.

System GMM (SYS-GMM) is the extended version of FD GMM, developed by Arellano and Bover (1995) and Blundell and Bond (1998). This method combines equations in first differences with equations in levels, using both levels and first differences in instruments to improve estimation efficiency and reduce bias.

$$Y_{it} = \alpha Y_{it-1} + \beta X_{it} + e_{it} \tag{2}$$

Here, Y_{it} represents the dependent variable, and Y_{it-1} is the lagged dependent variable. The independent variables X_{it} is a matrix of independent variables same as those in the FD-GMM model but in the SYS-GMM model this equation combines equations in first differences and in levels. Based on Equations 1 and 2, the variables and econometric model used are as follows:

$$\begin{aligned} lnPov_{it} = {} & \alpha\ lnPov_{it-1} + \beta_1\ LifeExpectancyi_{it} + \beta_2\ PrimarySchooling_{it} + \\ & \beta_3\ SecondarySchooling_{it} + \beta_4\ lnCapitaExp_{it} + \\ & \beta_5\ lnMandatoryExp_{it} + \beta_6\ Unemployment_{it} + \beta_7\ Water_{it} + \\ & \beta_8\ DCov19 + e_{it} \end{aligned} \tag{3}$$

where *i and t* denote individual regencies and time, respectively. $lnPov_{it}$ signifies poverty indicator which the natural logarithm of the number of poor people in each regency over time. The model includes a lagged dependent variable to capture the dynamic nature of poverty, acknowledging that current poverty levels are influenced by past ones. The dependent variable is the number of poor people rather than the poverty rate, following Xie et al. (2023) in the same System GMM framework. District-size differences are limited because the variable is in logarithmic form, and the first-difference transformation removes the time-invariant, size-related component.

The variables of interest include life expectancy ($LifeExpectancyi$) as a proxy for health quality and primary and secondary school enrolment rates ($PrimarySchooling$ and $SecondarySchooling$) representing education quality. To strengthen the estimation results, the control variables used are per capita expenditure ($lnCapitaExp_{it}$) as a proxy for economic well-being, government spending on education and health per capita ($lnMandatoryExp_{it}$), the open unemployment rate ($Unemployment$), access to clean water ($water$), and a dummy variable for the COVID-19 pandemic ($DCov19$).

This study employs both FD-GMM and SYS-GMM models with one-step and two-step estimation procedures. The GMM method is considered more appropriate because it can produce unbiased parameter estimates and detect issues of omitted variable bias or measurement errors (Apergis & Ozturk, 2015). Therefore, the results from each model and estimation are used for comparison to select the best model that satisfies all the assumptions and tests in the GMM panel data framework.

Results

A summary of the results for the Fixed Effects Model (FEM), Ordinary Least Square (OLS), First Difference GMM (FD GMM) and System GMM (SYS GMM) is

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presented in Table 1. The robustness check between fixed effects and sys GMM indicates that there were no changes in the significance of the three main independent variables: life expectancy, primary schooling, and secondary schooling. This indicates that the model used is robust and that the estimation can be continued. Due to the endogeneity problem, the results of the fixed or random effects may be biased. Therefore, the study employs both FD-GMM and SYS-GMM models with one-step and two-step estimation procedures.

Table 1. Summary of Regression

Variable	Dependent Variable: lnPOV					
	FEM	OLS	FD_1Step	FD_2Step	SYS_1Step	SYS_2Step
L.lnPOV	0.431***	0.982***	-0.380***	-0.410***	0.977***	0.934***
	(0.085)	(0.006)	(0.076)	(0.110)	(0.058)	(0.056)
LE (in years)	0.003	-0.000	-0.032	-0.048	-0.005	-0.002
	(0.013)	(0.002)	(0.019)	(0.036)	(0.012)	(0.016)
Primary Schooling %	-0.006***	-0.007***	-0.005**	-0.004	-0.010***	-0.010***
	(0.002)	(0.001)	(0.002)	(0.003)	(0.002)	(0.002)
Secondary Schooling %	-0.002***	-0.000	-0.000	-0.000	-0.003***	-0.003**
	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
lnCapitaExp	-0.244*	0.012	-0.289	-0.143	0.165	0.143
	(0.141)	(0.019)	(0.204)	(0.336)	(0.122)	(0.149)
lnMandatoryExp	-0.005	-0.012**	-0.006	-0.008	-0.016***	-0.015**
	(0.006)	(0.005)	(0.004)	(0.008)	(0.006)	(0.007)
Unemployment %	0.005*	-0.000	-0.001	-0.001	0.006*	0.006
	(0.003)	(0.001)	(0.001)	(0.002)	(0.003)	(0.004)
Water %	-0.000	-0.000	0.000**	0.000*	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
DCov19	0.005	0.022***	-0.003	-0.006	0.022**	0.019*
	(0.006)	(0.008)	(0.006)	(0.009)	(0.009)	(0.010)
Number of Obs	240	240	216	216	240	240
Number of Groups	24		24	24	24	24
Number of Instruments			18	18	27	27

Robust Standard Errors in Parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Auto-Serial Correlation Test

In the GMM framework, the Arellano-Bond test is used to check autocorrelation in the error terms. The Arellano-Bond test, also referred to as the non-autocorrelation test, is carried out by examining the autocorrelation in the second-order first difference. The desired outcome is the failure to reject the null hypothesis (H0), which would indicate the absence of autocorrelation issues and confirm the consistency of the estimation model equations.

Table 2. Arellano-Bond Test

Arellano-Bond test	FD-1step	FD-2step	SYS-1step	SYS-2step
AR (1)	0.0142	0.0240	0.0001	0.0002
AR (2)	0.0919	0.2585	0.7311	0.7147

As illustrated in Table 2, all GMM estimation methods, including FD-GMM and SYS-GMM in both one-step and two-step forms, display second-order z-probability values exceeding the 5 percent significance level. Therefore, it can be concluded that all GMM estimation models are free from bias due to autocorrelation in the error terms.

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Validity of the Instrument

To establish the consistency of the estimates obtained in the GMM estimation, the instrumental variables must have overall validity. The instrument validity test, or Sargan test, is a statistical procedure used to determine whether the instruments employed in the GMM estimation are valid. The Sargan test checks the exogeneity of all the instruments used.

Table 3. Sargan Test

Sargan test	FD-1step	FD-2step	SYS-1step	SYS-2step
Chi² (1)	85,069	20,295	136,452	21,334
Prob > chi²	0,000	0,009	0,000	0,211

Among the four GMM estimation models presented in Table 3, the SYS-GMM two-step model shows a chi-square probability value greater than the 5 percent alpha significance level, thus failing to reject the null hypothesis (H0). It can also be observed that the two-step estimation yields better chi-square probability values compared to the one-step estimation for both the FD-GMM and SYS-GMM models. According to Windmeijer (2005), two-step estimation provides more accurate coefficient values and addresses bias in instrument estimation.

Unbiassed Test

The unbiased test is conducted by comparing the lagged dependent variable in the GMM estimation with the results from the FEM and OLS estimations. The estimation results are considered unbiased when the lagged dependent variable falls between the values obtained from the FEM and OLS estimations.

Table 4. Unbiassed Test

Variable	FEM	FD-1step	FD-2step	SYS-1step	SYS-2step	OLS
L.lnPov	0.431^{***}	0.982^{***}	-0.380^{***}	-0.410^{***}	0.977^{***}	0.934^{***}
	(0.085)	(0.006)	(0.076)	(0.110)	(0.058)	(0.056)

From Table 4, it can be observed that the SYS-GMM model, both in one-step and two-step forms, passes the bias test, as the coefficient of the lagged dependent variable lies between 0.435 and 0.982. In contrast, the FD-GMM model exhibits a downward bias, as indicated by the lagged dependent variable's value being significantly lower than the fixed-effect model's estimation.

Selection of Dynamic Panel Data Models

The best model was selected based on the results that fulfilled the criteria given in the following table.

Table 5. Summary of GMM Test Results

Criteria	FD-1step	FD-2step	SYS-1step	SYS-2step
Arellano-Bond test	fulfilled	fulfilled	fulfilled	fulfilled
Sargan test	unfulfilled	unfulfilled	unfulfilled	fulfilled
Unbiassed test	unfulfilled	unfulfilled	fulfilled	fulfilled

Based on Table 5, the SYS GMM two-step model estimates are stated to be fulfilled. Thus, the regression results from this model are utilized for further discussion regarding the impact of human development quality on poverty.

Discussion

Life expectancy is used as a measure of health quality, representing the average number of years a person is expected to live, and reflects the overall health conditions of a population. Theoretically, better health should lead to higher productivity, as healthier individuals can work more effectively and for longer periods, which can help lift individuals and communities out of poverty. However, the study's findings indicate that the increase in life expectancy in South Sulawesi has not significantly impacted poverty reduction in the region. The regression results based on table 1 show a negative but not statistically significant coefficient for life expectancy, with a coefficient of -0.002. This could be due to several factors. First, the increase in life expectancy may not be accompanied by improvements in the quality of health. Second, higher health expenditures due to poor health conditions can offset the benefits of increased life expectancy. Third, this study highlights the increasing trend of health complaints, which could include mental health issues. Poor mental health can significantly affect productivity and economic stability.

The study concludes that while life expectancy is an important indicator of health, its increase alone does not significantly reduce poverty in South Sulawesi. This finding aligns with broader research indicating that poor health is both a cause and consequence of poverty, as it limits access to necessary resources and increases vulnerability to economic shocks. For instance, Gounder and Xing (2012) found that better health status significantly enhances productivity and reduces poverty levels. Similarly, Wei et al. (2023) noted that healthier populations are more capable of engaging in productive activities, reducing poverty levels. Additionally, Spada et al. (2024) highlighted that improved health outcomes can mitigate inequality and poverty by enhancing individuals' ability to participate effectively in the labor market. These studies collectively emphasize the critical role of health quality in poverty alleviation, supporting the need for policies that address both physical and mental health to sustainably reduce poverty.

Education is also considered among the basic sources of productivity and can be an agent quality of labor. Net enrolment rate for primary school and secondary reflecting the proportion of children of official school age who are enrolled in school. The regression results show that both primary schooling and secondary schooling have negative and statistically significant coefficients, with values of -0.01 and -0.003, respectively. The study's findings align with this theory, showing that increased access to education significantly reduces poverty in South Sulawesi. Primary education provides basic literacy and numeracy skills, which are essential for improving employability and productivity. Secondary education offers more advanced skills and knowledge, further enhancing job prospects and earning potential. Beyond statistical significance, the size of these effects is economically meaningful once read against actual variation in enrolment. A 10 percentage-point rise in primary enrolment is associated with about a 0.10 percent fall in the number of poor people, and the same rise in secondary enrolment with about a 0.03 percent fall (Table 1). The effect looks modest per point, but enrolment in South Sulawesi moves across a wide range, so closing the gap between the lowest and highest districts implies a far larger reduction than any single-point change suggests.

For instance, Ali and Ahmad (2013) found that higher education levels are associated with lower poverty rates in Pakistan. Similarly, Hofmacher (2021) demonstrated that additional years of schooling significantly reduce the likelihood of being classified as poor in Europe. This highlights the importance of educational policies and investments in human capital development for achieving sustainable poverty reduction. These findings are supported by broader research indicating that education not only enhances individual productivity but also contributes to overall economic growth and social development. Liu et al. (2021) found that different education levels have varying impacts on poverty reduction, with higher education levels having a more substantial effect. Marsinta et al. (2020) showed that education positively impacts household income and health, further reducing poverty.

Government spending on education and health per capita carries a negative and significant coefficient of -0.015; thus, a one percent rise in per capita mandatory spending is associated with about a 0.015 percent fall in the number of poor people. The results show that the budget of local governments, which is allocated to human capital, does reach its purpose of lowering poverty, consistent with Sabir and Aziz (2018), Wani and Dhami (2021), and Xie et al. (2023). To grow, the effect of the allocation of education and health spending should be evaluated each year so that it remains targeted. These studies collectively emphasize the critical role of education in poverty alleviation, supporting the need for policies that promote access to quality education at all levels to achieve long-term economic and social benefits.

On the other hand, per capita expenditure shows a positive coefficient but is not statistically significant. This finding contrasts with that of Sudarlan (2015), who found that increased income and expenditure reduce poverty risk. The relationship may run in reverse, as poorer districts can still record higher per-capita spending. It may also reflect an inequality effect, where early income growth widens the distribution before narrowing it (Sabir & Aziz, 2018), or spending directed toward consumption that does not raise the earning capacity. These readings fit the endogeneity of expenditure noted earlier, rather than contradicting the model. Xie et al. (2023) emphasized the importance of targeted public expenditure in improving human capital and reducing poverty.

The unemployment rate has a positive coefficient; therefore, its sign matches the theory and prior work, where higher unemployment raises poverty by lowering household income (Sofilda et al., 2013; Prasetyoningrum & Sulia, 2018). The effect is not significant in the SYS-GMM two-step model, but the direction still holds, as much of its influence is absorbed by the lagged dependent variable that captures poverty persistence. Therefore, the results support, rather than contradict, the established link between unemployment and poverty (Ngubane et al., 2023).

Access to clean water has a negative but insignificant coefficient. The descriptive statistics of the data show that access ranges widely across districts, from about 19 to nearly 100 percent), so the variable reflects sharp disparities rather than a steady level. It also measures access alone, not the quality or continuity of the supply. Any effect may further run indirectly through health; thus, part of its influence is already absorbed by the health and expenditure variables. The COVID-19 dummy variable has a positive and significant coefficient, highlighting the adverse economic

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impact of the pandemic, which increased poverty levels due to restricted economic activities and job losses.

Conclusion

In conclusion, this study underscores the importance of improving education quality and increasing enrolment rates to reduce poverty in South Sulawesi. Although higher life expectancy alone does not significantly impact poverty reduction, comprehensive health improvements are necessary to enhance productivity and economic stability. The findings also highlight the critical role of public spending on education and health, as well as the need to address unemployment to effectively combat it. These insights emphasize the need for holistic and targeted policies that address the multifaceted nature of poverty and promote sustainable development.

Based on the analysis results, the policy implications point to concrete steps in the fields of health and education. On health, the weak effect of life expectancy suggests that the local government should shift spending from longevity toward productive capacity by expanding occupational and mental health services, strengthening nutrition programmes for the working-age population, and using the rising trend in health complaints as a screening tool to direct district health budgets where they are most needed.

Regarding education, since the gains come from enrolment but remain small, policy should move from widening access toward raising learning quality through periodic assessment and training of teachers, curriculum reviews aligned with the changing labor market and the spread of AI, and targeted assistance that keeps students from poorer households enrolled. Both call for an annual evaluation of education and health budget allocation so that spending stays efficient and reaches the intended recipients.

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