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HEALTH INDICATORS AND HDI: PANEL EVIDENCE FROM WEST JAVA

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Abstract

Measuring regional development through the Human Development Index (HDI) carries an inherent limitation: its composite structure tends to smooth over disparities that persist at the sub-provincial level, especially in health. Drawing on a balanced panel of 27 districts and cities in West Java (2019–2023, N = 135), this paper examines whether four operational health inputs—sanitation coverage, national health insurance enrolment (JKN/BPJS), self-reported morbidity, and child undernutrition—translate into measurable HDI differences across time within each district. Secondary data from BPS, BPJS Kesehatan, and the Ministry of Health were analyzed using a fixed-effects estimator, chosen following Chow and Hausman specification tests; robust standard errors, clustered at the district level, were used to correct for heteroskedasticity and serial correlation. JKN/BPJS enrolment exerts the strongest influence ($\beta = 0.273$, $p < 0.01$), while child undernutrition consistently depresses HDI ($\beta = -0.011$, $p < 0.01$). Sanitation reaches significance, but its within-district coefficient is unexpectedly negative; morbidity is negative yet statistically insignificant. Together, the regressors account for roughly 45 percent of the within-district HDI movement. Accelerating JKN utilization quality and multi-sectoral undernutrition programs emerge as the highest-leverage entry points for local governments seeking to advance human development in West Java.

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INTRODUCTION

West Java recorded a provincial HDI of 73.74 in 2023, yet the figure conceals a striking internal range: individual district scores spanned from below 65 to above 80 in the same year (BPS Jawa Barat, 2024; Agustina et al., 2022). That gap— roughly 21 points between the most and least developed districts within a single province—illustrates a well-documented weakness of composite indices. The Human Development Index, constructed by UNDP to capture education, health, and material living standards in one number, offers an analytically convenient summary but inevitably trades granularity for legibility (Budihardjo et al., 2021; Sumiyarti et al., 2022).

Within the broader development literature, health has long been recognized as both a component and a driver of HDI. Todaro and Smith (2018) and the UNDP's 2019 Human Development Report situate access to health care at the core of capability expansion: without physical well-being, the returns to education and income are substantially curtailed. At the same time, aggregated health metrics can obscure the very inequities they aim to document. Bloom and Canning (2000) pointed to this bidirectional entanglement between health status and economic outcomes decades ago, and more recent work—including Mokdad et al. (2022) on provincial disease burden in Indonesia and Utami et al. (2025) on growth dynamics—reaffirms that sub-provincial variation is where policy-relevant heterogeneity predominantly lives. The implication is that researchers and practitioners need indicators that are both operationally measurable and directly amenable to government intervention, rather than relying solely on high-level composites.

The disruptions of the COVID-19 period sharpened this point considerably. Post-pandemic surveillance data from West Java show that year-on-year shifts in HDI did not track consistently with changes in sanitation access, health insurance enrolment, reported illness rates, or nutritional status—variables that district governments can realistically adjust through budgetary and programmatic choices (Irianti & Prasetyoputra, 2021; Satriani et al., 2022). Indonesia's Jaminan Kesehatan Nasional (JKN) scheme, which began operating in 2014 under BPJS Kesehatan, had enrolled roughly 278 million people—equivalent to 98.45 percent of the population—by the close of 2024, making it the world's largest single-payer health insurance program (BPJS Kesehatan, 2024).

However, near-universal enrolment does not straightforwardly equate to uniform health outcomes. Kosasih et al. (2022), in a retrospective cohort study conducted in Bandung City, West Java, and published in BMC Public Health, established that health-seeking behavior remained stratified by socioeconomic status even after JKN implementation, with lower-income groups less likely to utilize formal care despite formal coverage. This gap between enrolment and effective utilization implies that cross-district variation in coverage rates may capture institutional differences that generate cross-dimensional spillovers onto broader human development components—a dynamic that this paper evaluates empirically.

From a nutritional standpoint, Indonesia's situation warrants particular attention. Stunting prevalence was recorded at 21.5 percent in 2023 by the national nutrition survey (SSGI), leaving the government well short of its 14 percent target for 2024 (Ministry of Health, 2023). Ayuningtyas et al. (2022) analyzed Riskesdas data across all 514 Indonesian districts and, publishing in Nutrients (Scopus Q1), found that geographic and socioeconomic disparities in child undernutrition are substantial, with poverty rates, female education levels, and access to water and sanitation emerging as the strongest district-level correlates. West Java, despite its relatively advanced provincial economy, harbors considerable intra-provincial variation in the prevalence of undernutrition, making it a relevant test case for examining how nutritional conditions translate into HDI differences at the district scale.

A survey of existing work reveals that most empirical studies on HDI determinants in Indonesia operate at the provincial level and tend to treat health as a single-dimensional construct. Tyas and Sukartini (2022) used panel data from 34 provinces (2014–2021) to show that health infrastructure and protein consumption contribute significantly to HDI components, though their analysis cannot address within-province heterogeneity. Nurlina et al. (2023) applied an ARDL framework to national data spanning 1990–2021, identifying education expenditure and economic growth as the dominant long-run drivers while noting the relatively muted short-term signal from health spending. Specifically on sanitation, Hariani and Ekaria (2023) found a significant indirect effect on HDI through poverty mediation in Eastern Indonesia. Erlangga et al. (2019), using the longitudinal IFLS panel, documented that JKN enrolment significantly increased inpatient utilization, particularly among the contributory group—a utilization pathway with direct implications for the health dimension of HDI.

In Central Sulawesi, Pakpahan et al. (2024) reported that malnutrition had a negative but statistically inconclusive coefficient. In contrast, Agustina et al. (2022) focused on West Java and limited their set of variables to government expenditures and poverty. None of these studies simultaneously models the four operational indicators—namely health insurance coverage, sanitation access, undernutrition prevalence, and reported morbidity that front-line health governance directly controls. That is the gap this paper addresses.

Theoretically, the paper is grounded in Sen's (1999) capability approach. Sen's argument—that genuine development consists in expanding what people can do and be, not merely in raising incomes—implies that clean sanitation, health insurance coverage, and adequate nutrition function as foundational capabilities: their absence forecloses participation in education and labor markets regardless of income levels. Empirically, the unit of analysis comprises all 27 districts and cities in West Java from 2019 to 2023, yielding a balanced panel of 135 observations.

Three questions organize the inquiry: first, what is the trajectory of HDI and each health indicator across West Java's districts in this period? Second, which indicator exerts the strongest within-district influence on HDI movement? Third, do sign and magnitude remain stable across estimation approaches? The study contributes post-pandemic micro-regional evidence that integrates four health variables simultaneously, and translates its findings into actionable priorities aligned with SDG 3 and SDG 6.

RESEARCH METHODS

The study adopts a quantitative, cross-sectional time-series design built around a balanced panel covering all 27 districts and cities in Jawa Barat Province for the years 2019 through 2023, yielding N = 27 units, T = 5 periods, and 135 total observations. Because every administrative unit in the province is included, no sampling procedure was necessary. The dependent variable—the district-level HDI—was obtained from official BPS publications. While the HDI fundamentally incorporates a health outcome dimension via life expectancy, utilizing operational health inputs (JKN, sanitation, and undernutrition) as regressors remains conceptually justified.

These inputs do not merely mirror biological health outcomes; instead, they function as structural policy levers that generate cross-dimensional spillovers. For example, JKN coverage offers financial risk protection that directly insulates household consumption (the income dimension of HDI). In contrast, child nutrition heavily determines early childhood cognitive capacity and subsequent school attainment (the education dimension).

Consequently, this framework evaluates how institutional health interventions shift broader human development trajectories rather than introducing a tautological artifact. Among the four health regressors, access to improved sanitation and the self-reported morbidity rate were drawn from BPS-SUSENAS; JKN/BPJS enrolment coverage was drawn from BPJS Kesehatan records, cross-checked against SUSENAS; and child undernutrition prevalence was drawn from the Ministry of Health's Riskesdas and SSGI surveys. Where the reporting cycles of different sources did not align perfectly, the nearest available year was matched, or, where necessary, bounded linear interpolation was applied within the 0–100 percent range to maintain series integrity.

All variables were entered into the model in natural-log form to attenuate right-skewness in the distributions and to allow the estimated coefficients to be read directly as elasticities. The structural equation estimated is:

$$\ln(HDI_{it}) = \alpha_i + \beta_1 \ln(JK_{it}) + \beta_2 \ln(SNS_{it}) + \beta_3 \ln(KS_{it}) + \beta_4 \ln(GK_{it}) + \varepsilon_{it} \quad \ldots(1)$$

The term α_i absorbs all time-invariant, district-specific factors (institutional capacity, geographic endowments, cultural norms) that might otherwise confound the health-HDI relationship. ε_{it} is the remaining idiosyncratic disturbance. Specification choice followed a sequential testing strategy: the Chow test compared pooled OLS against fixed effects, and the Hausman test adjudicated between fixed and random effects. Prior to finalizing the error structure, the Breusch-Pagan test was used to check for heteroskedasticity, and Wooldridge's test was used to examine first-order serial correlation in the panel errors; both concerns proved statistically warranted, motivating the use of robust standard errors clustered at the district/city level throughout.

Results from pooled OLS and random-effect estimators are presented alongside the preferred FE estimates as robustness benchmarks. While a dynamic panel specification utilizing lagged independent variables represents a theoretically plausible causal alternative, a static Fixed Effects model is strictly retained here due to the small scale of our panel (N=27, T=5), which introduces severe mathematical constraints and a high risk of instrument proliferation under generalized method of moments (GMM) environments

Table 1. Variable Description and Descriptive Statistics

Variable	Definition	Scale	Mean	SD	Min	Max
HDI	BPS composite index (health, education, standard of living)	0–100	72.14	3.82	61.79	83.24
Sanitation (SNS)	% households with improved sanitation access (SUSENAS)	Ratio (%)	79.36	12.41	48.20	98.70
Health Insurance (JK)	% population covered by JKN/BPJS (SUSENAS / BPJS Kesehatan)	Ratio (%)	68.45	14.27	32.10	97.80
Morbidity (KS)	% population reporting illness in survey reference period (SUSENAS)	Ratio (%)	11.23	3.15	4.80	19.60
Undernutrition (GK)	Prevalence of under-5 undernutrition — Riskesdas/SSGI	Ratio (%)	7.84	3.09	1.90	17.30

Source: BPS, BPJS Kesehatan, Kemenkes RI; authors' compilation. Statistics computed over 135 pooled district-year observations.

RESULTS AND DISCUSSION

Before interpreting the coefficients, it is worth pausing to consider what the descriptive statistics in Table 1 reveal. Across the 135 district-year cells, HDI spans a substantial range of 21.45 points, from a minimum of 61.79 to a maximum of 83.24, and JKN coverage runs from barely one-third of the district population to near-total enrolment (32.10 to 97.80%).

Undernutrition prevalence is similarly dispersed, ranging from a low of 1.90 percent in the best-performing districts to 17.30 percent in the most affected areas. This breadth of variation is not a statistical artifact; it reflects genuine structural inequalities across West Java's 27 districts, which justify the panel approach and underscore why aggregate provincial figures can be misleading. The Breusch-Pagan test ($\chi^2(1) = 18.43$, $p = 0.000$) and the Wooldridge serial correlation test ($F(1,26) = 9.17$, $p = 0.005$) both yielded highly significant results, confirming the presence of heteroskedastic and autocorrelated errors that warrant the use of cluster-robust standard errors.

Table 2. Model Selection and Diagnostic Test Results

Test / Statistic	Value/Prob.
Chow Test (FE vs. Pooled OLS)	
F-statistic	277,54
Prob > F	0,0000***
Hausman Test (FE vs. RE)	
Chi² statistic	35,63
Prob>Chi²	0,0000***
Breusch-Pagan Test (Heteroskedasticity)	
Chi² (1)	18,43
p-value	0,0000***
Wooldridge Test (Serial Autocorrelation)	
F(1, 26)	9,17
p-value	0,0050***

Note: *** significant at 1%. Source: Authors' own calculation.

Both specification tests unambiguously favor the fixed-effect estimator. The Chow F-statistic of 277.54 ($p = 0.0000$) rules out pooled OLS, and the Hausman chi-squared of 35.63 ($p = 0.0000$) rejects the random-effect alternative at the 1 percent significance level. On substantive grounds, the fixed-effect structure is also the more defensible choice: West Java's districts differ in ways—administrative history, local political economy, geographic isolation, dominant livelihoods—that are stable over the five-year window but almost certainly correlated with both health investment levels and HDI outcomes.

Pooling across districts without accounting for these latent differences would introduce severe omitted-variable bias; the fixed-effect transformation eliminates them by construction. Furthermore, the diagnostic block in Table 2 confirms that the baseline model errors suffer from heteroskedasticity (Breusch-Pagan χ^2 = 18.43, p = 0.0000) and serial correlation (Wooldridge F = 9.17, p = 0.0050), fully validating the decision to base all substantive interpretations on the cluster-robust standard error covariance matrix.

Table 3. Regression Estimates — Dependent Variable: ln(HDI)

Variable	FE (Robust)	Pooled OLS	Random Effect
ln(JK) — Health Insurance	0,2731***	0,2415***	0,2598***
	(0,0093)	(0,0112)	(0,0102)
ln(SNS) — Sanitation	-0,0047**	0,0231***	0,0189**
	(0,0208)	(0,0078)	(0,0091)
ln(GK) — Undernutrition	-0,0108***	-0,0092***	-0,0101***
	(0,0035)	(0,0029)	(0,0033)
ln(KS) — Reported Morbidity	-0,0473	-0,0311	-0,0398
	(0,0333)	(0,0298)	(0,0318)
Constant	3,9810***	3,1240***	3,6150***
	(0,0857)	(0,1104)	(0,0932)
R^2	0,4509	0,3871	0,4118
Prob > F	0,0000	0,0000	0,0000
Observations	135	135	135

Note: *** p<0.01, ** p<0.05, * p<0.10. Robust clustered SE in parentheses.

Source: Authors' own calculation.

Given the temporal boundaries of our dataset (T=5), these Fixed Effects parameters must be interpreted strictly as short-run, within-district associations arising from immediate operational fluctuations, rather than as permanent, long-term structural developmental effects. Human development accumulation, structural nutritional improvements, and large-scale sanitation infrastructure typically operate on generational timelines. Additionally, because the 2019–2023 window heavily encapsulates the severe socioeconomic and health system disruptions induced by the COVID-19 pandemic, the short-term sensitivity of these parameters underscores localized institutional and policy adjustments during a crisis period rather than stable, long-run structural equilibria.

The FE model passes the joint significance test comfortably (Prob > F = 0.000). The within-R^2 of 0.4509 indicates that roughly 45.09 percent of the year-to-year movement in district HDI is accounted for by the four health variables alone—a meaningful share given that the education and income components of HDI, which are not modeled here by design, inevitably absorb a substantial portion of within-district variance. Sign and significance patterns are consistent across FE, Pooled OLS, and RE estimators, with the partial exception of sanitation discussed below, lending credibility to the core findings.

The health insurance variable (ln_JK) yields the largest elasticity in the model: a one percent rise in JKN coverage corresponds to a 0.2731 percent gain in district HDI ($p < 0.01$), and this result is highly stable across FE, Pooled OLS, and RE specifications. Two reinforcing mechanisms make this plausible. On the demand side, insurance enrolment removes out-of-pocket cost as a barrier to care-seeking; Erlangga et al. (2019) estimated, using IFLS panel waves, that JKN membership raised inpatient utilization rates significantly—particularly for contributory members who gained access to services they had previously foregone for financial reasons.

This increase in utilization feeds directly into the life-expectancy component of the HDI through reduced mortality from treatable conditions. On the behavioral side, Kosasih et al. (2022), drawing on fieldwork in Bandung, West Java, found that JKN adoption prompted a shift in how community members responded to acute and chronic illness episodes, with formal healthcare contacts rising across both educated and less-educated subgroups.

Taken together, these demand-side and behavioral channels help explain why within-district expansions in JKN coverage consistently register as HDI improvements, a finding that is consistent with The Lancet's (2018) assessment of UHC progress in Indonesia and with Todaro and Smith's (2018) theoretical framing of insurance as a capability-enabling institution.

The undernutrition variable (ln_GK) carries a negative and highly significant coefficient of −0.0108 ($p < 0.01$) across all three estimators, making it the second most influential predictor in the model. Its sign requires little interpretive effort: poorly nourished children enter school later, learn less efficiently, and face higher rates of morbidity and absenteeism throughout childhood—a cascade of disadvantage that compresses both the education and life expectancy components of the HDI well into adulthood (Ministry of Health, 2023). Ayuningtyas et al. (2022), studying disparities in child undernutrition across 514 Indonesian districts in Nutrients, showed that poverty intensity and female educational attainment are the dominant district-level correlates of wasting and stunting—suggesting that nutrition improvements achieved through income support or women's education would carry HDI returns well beyond the nutritional channel alone.

The negative but non-significant coefficient for malnutrition found by Pakpahan et al. (2024) in Central Sulawesi may reflect that province's different baseline nutritional profile and a shorter panel window; the West Java result here, with greater cross-district variance and a standardized measurement instrument, yields a statistically cleaner estimate. The implication for district governments is concrete: prioritizing stunting reduction in the ten highest-prevalence kabupaten would, on these estimates, generate measurable within-period gains in HDI.

The sanitation coefficient (ln_SNS) is where the fixed-effect and cross-sectional estimates diverge most visibly. Pooled OLS and RE both return positive and significant values (beta equals 0.0231 and beta equals 0.023, respectively, $p < 0.01$ or $p < 0.05$), consistent with the literature's conventional story that districts with better sanitation infrastructure also score higher on HDI (Hariani & Ekaria, 2023). The FE estimate, however, flips negative ($\beta = -0.005$, $p < 0.05$). This sign reversal deserves careful analysis rather than dismissal. Within the FE transformation, only the within-district time variation identifies the coefficient; between-district differences are entirely absorbed by the district fixed effects.

Several non-exclusive explanations account for the pattern. First, many West Java districts already had sanitation coverage exceeding 75 percent at the start of the observation window (Table 1: mean 79.4%, min 48.2%), so marginal increases in already well-served districts may yield diminishing HDI returns—a saturation dynamic. Second, public health pathways from improved sanitation to lower morbidity and higher life expectancy operate through multi-year lags driven by epidemiological cycles and behavioral adaptation; within a five-year contemporaneous window, these lags may not yet be captured (Irianti & Prasetyoputra, 2021).

Third, the SUSENAS self-reporting of "improved" sanitation is known to vary in interpretation across enumerators and respondents, particularly where household toilet quality is borderline; this classical measurement error, amplified under the within-district FE transformation, can attenuate or reverse the estimated sign (Purwaningsih et al., 2021). The policy lesson is not that sanitation is unimportant—the cross-sectional evidence affirms that it is—but rather that infrastructure investment alone, without sustained behavioral change communication, yields limited within-period HDI gains.

Reported morbidity (ln_KS) is consistently negative but never reaches conventional significance thresholds in any specification (FE: β = -0.0473; Pooled OLS: -0.0311; RE: -0.0398; all $p > 0.10$). The most plausible explanation is a reporting paradox inherent to survey-based morbidity data. In districts where JKN coverage is high, and health literacy has improved alongside it, residents are more inclined to identify and report symptoms—precisely because they are more likely to seek formal care.

This creates an upward measurement bias in reported morbidity that partially offsets the underlying negative relationship between actual illness burden and HDI. Replacing self-reported morbidity with objective indicators—facility-based disease incidence, age-standardized mortality rates, or hospitalizations per capita—would likely sharpen the estimated coefficient in future work, as Mokdad et al. (2022) demonstrated in their province-level analysis of Global Burden of Disease data.

Stepping back, the results converge on a clear hierarchy of health-policy levers. JKN/BPJS coverage is the strongest within-district driver of HDI among the four indicators examined; undernutrition is the strongest drag. Sanitation matters—particularly across districts—but infrastructure expansion must be paired with education and behavioral interventions to yield near-term HDI returns. Morbidity, as measured through SUSENAS, does not currently offer a reliable empirical signal. These gradients are directly relevant to the allocation of discretionary budgets in district RPJMD plans and to provincial monitoring of district performance against SDG 3 and SDG 6 targets.

CONCLUSION

This study set out to answer whether operational health inputs—sanitation coverage, JKN/BPJS enrolment, reported morbidity, and child undernutrition—meaningfully shift HDI trajectories within West Java's 27 districts over the 2019–2023 period. A fixed-effects panel model, supported by diagnostic tests and triangulated with pooled OLS and random-effects benchmarks, yields three substantive findings. JKN/BPJS coverage emerges as the strongest positive predictor, with utilization and financial protection mechanisms serving as the primary transmission channels.

Child undernutrition represents the most severe drag on human development, consistent with the long-term cognitive and productivity costs documented in literature and aligned with the capabilities framework. Sanitation exhibits significant cross-sectional variance but shows a marginal negative within-district trend under fixed effects, suggesting potential saturation effects and the structural limits of a five-year window in capturing long-term infrastructure lags. Reported morbidity carries no statistically meaningful within-district signal, most likely because self-reported survey responses conflate actual illness burden with heightened health awareness.

Crucially, this study acknowledges a methodological caveat regarding potential endogeneity. The relationship between JKN enrollment and HDI may be bidirectional, as economically advanced districts with higher HDI baselines naturally possess superior institutional and fiscal capacities to expand universal health coverage. Due to the structural constraints of a relatively short panel framework, advanced instrumental-variables or dynamic GMM estimators could not be implemented robustly without introducing a severe risk of instrument proliferation.

Consequently, while our Fixed Effects model successfully absorbs time-invariant district heterogeneities, the coefficients should be interpreted as short-run within-district associations driven by immediate operational fluctuations, rather than long-term structural developmental equilibria. The remaining variation in within-district human development is attributable to broader structural determinants such as education spending, income levels, and institutional quality, which future research should incorporate alongside a dynamic panel specification to capture intertemporal lags.

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