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RESEARCH ARTICLE

Measuring Human Capital in Indonesia Using an Adapted World Bank HCI Framework

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ABSTRACT

Despite the growing recognition of human capital as a key foundation of development, Indonesia still lacks a multidimensional provincial measure. This study develops a Human Capital Index (HCI) for Indonesian provinces based on the World Bank HCI framework and examines its spatial and temporal patterns during 2011–2019. The index is constructed using normalized indicators representing survival, schooling, and health dimensions, namely Measles Immunization, Expected Years of Schooling, Mean Years of Schooling, National Examination Score, and Life Expectancy. The study applies min–max normalization, composite index construction, Sturges' Rule classification, robustness testing, Global Moran's I, Pearson correlation, and temporal disparity analysis. The results show that provincial HCI is generally concentrated in the middle range, but disparities remain across provinces. DI Yogyakarta records the highest average HCI, while Papua records the lowest. The index is robust under alternative weighting scenarios. Spatial analysis shows no significant global clustering for composite HCI, although Measles Immunization and Life Expectancy exhibit significant spatial clustering. Furthermore, temporal analysis indicates persistent interprovincial disparities during this period. Overall, this HCI can serve as a diagnostic tool for targeted human capital policy.

Contribution/Originality: This study contributes by developing a Human Capital Index for Indonesia based on the World Bank HCI framework. Unlike previous studies that often rely on single human capital indicators, this study combines survival, schooling, and health dimensions to provide a more comprehensive measure for

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provincial comparison and policy diagnosis.

1. Introduction

Human capital is widely recognized as a fundamental determinant of long-term economic growth and development (Sorto-Bueso et al., 2026; Gyimah-Brempong, 2002). Early human capital theory emphasizes that investment in education, skills, and health increases individual productivity and, in turn, contributes to broader economic development (Schultz, 1961; Becker, 1964). This view has also been reinforced in contemporary global development agendas, particularly the Sustainable Development Goals, which emphasize poverty reduction, health, quality education, and decent work as the objectives of sustainable development (United Nations, 2015). In this context, human capital should not be understood merely as schooling attainment, but as a broader set of capabilities that enables individuals to survive, learn, remain healthy, and participate productively in the economy.

Measuring human capital is challenging because there is still no clear consensus on the most appropriate indicators for measuring it (Chang & Shi, 2016; Zhang et al., 2023). Many empirical studies still rely on single indicators, such as years of schooling, school enrollment rate, life expectancy, and others. Although these indicators are useful, they do not fully capture the multidimensional nature of human capital (Zhang et al., 2023). Education is one of the main channels through which human capital is accumulated, but its contribution cannot be adequately represented by schooling participation or educational attainment alone. What matters is not only how long individuals remains in school, but also the extent to which schooling improves their cognitive skills and knowledge. Hanushek & Woessmann (2007) distinguish this issue into two dimensions: the quantity and the quality of education. Although educational quantity, commonly measured by years of schooling or enrolment rates, is relatively simple to observe, relying solely on these indicators may lead to an incomplete assessment of human capital formation (Hanushek & Woessmann, 2008). Therefore, incorporating the quality of education, often proxied by student test scores, is essential for evaluating whether schooling effectively translates into human capital. Beyond schooling, human capital measurement also needs to incorporate survival and health-related dimensions, since future productivity depends not only on learning outcomes, but also on individuals' ability to survive and remain healthy throughout the life cycle.

In Indonesia, this measurement issue is particularly relevant because improvements in educational access do not necessarily imply equal progress in learning quality, health-related capabilities, and future productivity. Measuring human capital at the provincial level is important for supporting more targeted policy formulation in a geographically diverse country such as Indonesia. Therefore, the World Bank Human Capital Index (HCI) further reinforces this multidimensional perspective by combining survival, schooling, and health indicators to estimate the human capital that a child can expect to accumulate by adulthood (Kraay, 2019). Nevertheless, applying the original HCI World Bank at the Indonesian provincial level is not straightforward due to limitations in data availability and consistency. Hence, an adapted framework is needed to measure human capital across provinces using available and theoretically relevant indicators.

Despite the importance of human capital for long-term economic growth and development, provincial-level measurement of human capital in Indonesia remains

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limited. Existing studies often focus on single indicators, while fewer studies construct a multidimensional index that allows comparison across provinces and over time, particularly in identifying spatial differences and the persistence of interprovincial disparities. Accordingly, this study addresses this gap by developing an adapted HCI for Indonesian provinces and using it to examine the spatial and temporal patterns of human capital during 2011–2019.

1.1. Research Objectives

This study aims to develop Human Capital Index for Indonesian provinces based on the World Bank HCI framework and to examine the spatial and temporal patterns of human capital across Indonesia during 2011–2019. Specifically, the objectives of this study are:

i. To construct Human Capital Index for Indonesian provinces using normalized indicators of survival, school, and health.
ii. To analyze the spatial distribution of provincial human capital and identify the indicators most closely associated with differences in HCI across provinces.
iii. To examine the temporal patterns of HCI during 2011–2019, including changes in average human capital performance and interprovincial disparities over time.

1.2. Significance of the Study

Given the research gaps outlined above, this study advances the literature through several contributions. This study develops a provincial Human Capital Index for Indonesia using an adapted World Bank HCI framework. Unlike studies that rely on single indicators such as Mean Years of Schooling or educational attainment, this study combines survival, schooling, and health dimensions to provide a more comprehensive measure of human capital. From a policy perspective, the adapted HCI can serve as a diagnostic tool for identifying provincial strengths and weaknesses in human capital dimensions. The findings can support more targeted regional planning, budget prioritization, and monitoring of human capital policies, particularly for provinces with persistently low HCI values.

2. Literature Review

2.1. The Theory of Human Capital

Human capital theory provides a foundational explanation of how investments in people contribute to productivity, earnings, and long-term economic development. Schultz (1961) argues that skills, knowledge, and physical ability should be treated as a form of capital because they are produced through deliberate investment and can improve the quality and productivity of human effort. Becker (1962) further formalizes this idea by defining human capital investment as activities that embed productive resources in individuals and raise their future real income. These investments include schooling, on-the-job training, medical care, and the acquisition of information, all of which involve costs in the present but are expected to generate future returns through higher productivity and earnings. Mincer (1974) extends the theory empirically by linking schooling and work experience to earnings differentials. His analysis shows that years of schooling are important, but they do not fully explain income differences unless post-school investments, especially experience and training, are also considered. Together, these contributions establish human capital as a multidimensional concept that includes

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education, health, training, and experience. Therefore, this theory supports the view that measuring human capital requires more than a single education indicator.

2.2. Measuring Human Capital

Measuring human capital remains a central challenge in empirical development studies because there is no widely accepted consensus on which indicators best represent it (Chang & Shi, 2016; Zhang et al., 2023). This difficulty arises from the fact that human capital is not a single observable attribute, but a complex and multidimensional construct that includes education, skills, health, cognitive ability, and other capabilities that shape individual productivity (Van den Berg, 2001; Zhang et al., 2023; Lasmane et al., 2025). From this perspective, human capital can be understood as a latent variable: it cannot be directly observed, but must be inferred through measurable indicators that approximate its underlying dimensions (Hanushek & Woessmann, 2008; Hanushek & Woessmann, 2012a; Hanushek & Woessmann, 2012b).

Hanushek & Woessmann (2012a) highlight the limitations of using mean years of schooling as a proxy for human capital. Although this indicator captures the duration of formal education, it does not necessarily reflect the quality of learning or the actual skills and knowledge acquired by students. The same number of schooling years may produce different levels of human capital because educational outcomes are shaped by differences in teaching quality, curriculum standards, school infrastructure, and the overall effectiveness of education systems across countries. For instance, students who complete the same length of schooling in countries with high-performing education systems may acquire substantially stronger competencies than students in countries where the quality of education is weaker.

The evolution of human capital measurement reflects a growing awareness of the limitations of relying on a single indicator. Studies in the 1990s commonly used school enrolment rates as a proxy for human capital (Barro & Sala-i-Martin, 1990; Barro et al., 1991; Mankiw et al., 1992; Benhabib & Spiegel, 1994; Card, 1999), while research in the 2000s increasingly shifted toward mean years of schooling to represent educational attainment more directly (Kalaitzidakis et al., 2001; Wilson & Briscoe, 2004). In the early 2010s, test scores began to receive greater attention because they capture the quality of learning rather than merely the quantity of schooling (Hanushek & Woessmann, 2007; 2008; 2012a; 2012b; 2016; Affandi et al., 2019; Zhang et al., 2023). This shift indicates that, over the past three decades, scholars have become more attentive to the selection of indicators in measuring human capital. As the limitations of single proxies became more evident, researchers increasingly turned to index-based approaches. Unlike measures such as enrolment rates or mean years of schooling, a composite index allows human capital to be represented as a multidimensional construct that incorporates several related dimensions (Duisen et al., 2025; Lasmane et al., 2025; Nazamuddin et al., 2025; Sari & Tiwari, 2024; Yadav & Mohapatra, 2023; Windhani et al., 2023). Therefore, recent studies have increasingly employed human capital indices to provide a more comprehensive measure of human capital and to better capture differences in education, skills, health, and productive capacity.

Recent studies show that human capital indices have been constructed using different dimensions, indicators, and levels of analysis. Lasmane et al. (2025), for example, developed a human capital index for Latvia during 2014–2023 by combining labour market, education, and health dimensions using min–max normalization. Yadav &

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Mohapatra (2023) adapted the World Bank HCI framework for Indian states and Union Territories, although their index used only four of the five original HCI indicators. In Indonesia, Nazamuddin et al. (2025) constructed a district-level HCI for 2019–2023 based on education and health indicators, but the index did not incorporate learning quality or cognitive skills. Sari & Tiwari (2024) applied the World Bank HCI framework at the provincial and district levels in Indonesia, but their analysis was limited to two years, 2013 and 2018, making it less able to capture annual dynamics. Meanwhile, Windhani et al. (2023) measured human capital at the regency and municipality levels using a modified AHDI framework that incorporated education, economy, longevity, gender empowerment, democracy, and health quality. These studies indicate that human capital index construction is highly context-dependent and shaped by data availability, methodological choices, and the level of territorial analysis.

2.3. World Bank HCI Framework and Adaptation

The World Bank Human Capital Index provides one of the most influential multidimensional frameworks for measuring human capital. The index was developed to estimate the amount of human capital that a child born today can expect to attain by adulthood, given the prevailing risks of poor health and poor education. In the original framework, the HCI consists of three main components: survival, schooling, and health. The survival component reflects the probability that children survive until the age at which formal human capital accumulation begins. The schooling component combines the quantity of education, measured by expected years of schooling, with the quality of education, measured through harmonized test scores. The health component is represented by adult survival rates and the fraction of children under five who are not stunted (World Bank, 2018; World Bank, 2020).

A key strength of the HCI framework is that it does not measure human capital merely through inputs, such as public spending on education or health, but through outcomes that are more closely related to future productivity. The World Bank emphasizes that the HCI ranges from 0 to 1 and represents the expected productivity of a future worker relative to a benchmark of complete education and full health (World Bank, 2018; World Bank, 2020). This makes the HCI useful not only as a summary measure of human capital, but also as a diagnostic tool for identifying weaknesses in survival, schooling, and health outcomes.

However, applying the original World Bank HCI directly at the Indonesian provincial level is not straightforward. Several original indicators, including under-five mortality, harmonized international test scores, adult survival rate, and stunting, are not consistently available at the provincial level for the full period of analysis. Therefore, an adapted framework is required to preserve the multidimensional logic of the HCI while adjusting it to Indonesia’s data availability. In this study, the survival dimension is proxied by measles immunization; the schooling dimension is represented by expected years of schooling, mean years of schooling, and national examination scores; and the health dimension is proxied by life expectancy. This adaptation allows the index to remain theoretically aligned with the World Bank HCI framework while enabling comparable measurement across Indonesian provinces during 2011–2019.

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3. Data and Methodology

This study constructs an adapted Human Capital Index (HCI) for 34 Indonesian provinces during 2011–2019. The period is selected to ensure comparability across indicators, particularly because the National Examination Score, used as a proxy for learning outcomes or the quality of education, is no longer consistently available after the discontinuation of the national examination system in 2020. The index adapts the World Bank HCI framework, which conceptualizes human capital through three core dimensions: survival, schooling, and health (World Bank, 2018; World Bank, 2020).

In the original framework, these dimensions are represented by indicators such as survival to age five, expected years of learning-adjusted schooling, adult survival, and child stunting. However, applying the original framework directly at the Indonesian provincial level is not feasible because several indicators are not available. Therefore, this study uses theoretically relevant proxy indicators that are comparable across provinces and available throughout the period of analysis. The adaptation is designed to preserve the multidimensional logic of the World Bank HCI while adjusting the measurement to the Indonesian subnational data context. Table 1 summarizes the original HCI components and the adapted indicators used in this study.

Table 1: World Bank HCI Framework and Adaptation

World Bank HCI Component	Original World Bank HCI Indicator	Adapted Indicator in This Study	Rationale
Survival	Probability of survival to age 5 / under-five mortality rate	Measles Immunization	Under-five mortality is not consistently available at the provincial level for the full period of analysis; measles immunization reflects child health protection and is closely related to child survival.
Schooling	Expected years of school	Expected Years of Schooling	This indicator is available at the provincial level and captures the expected quantity of formal education.
Schooling	Learning-adjusted schooling / harmonized test scores	National Examination Score	International test scores such as PISA are not available at the provincial level; national examination scores are used as a proxy for learning outcomes.
Schooling	—	Mean Years of Schooling	This indicator is added to capture the accumulated stock of education among the adult population, complementing the forward-looking nature of expected years of schooling.
Health	Adult survival rate and fraction of children under five not stunted	Life Expectancy	Adult survival rate data is not available in Indonesia, while stunting data are not consistently available at the provincial level for 2011–2019; life expectancy is used as a proxy for overall health conditions.

Source: Author's adaptation based on the World Bank HCI framework (World Bank, 2018, 2020)

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The adapted HCI consists of five indicators. The survival dimension is represented by Measles Immunization (MI), the schooling dimension is represented by Expected Years of Schooling (EYS), Mean Years of Schooling (MYS), and National Examination Score (NES), while the health dimension is represented by Life Expectancy (LE). All indicators are transformed into a 0–100 scale to ensure comparability across different units of measurement. Since all selected indicators are positive indicators, where higher values indicate better human capital performance, the normalization is conducted using the following min–max formula:

$$I_{ji}^{t} = \frac{x_{ji}^{t} - x_{j}^{min}}{x_{j}^{max} - x_{j}^{min}}$$

where I_{ji}^{t} is the normalized value, x_{ji}^{t} is the original value, x_{j}^{min} is the minimum value, and x_{j}^{max} is the maximum value of each indicator. Min–max normalization is commonly used in composite index construction because it allows indicators with different units to be transformed into a comparable scale without changing their relative position (OECD et al., 2008). Table 2 presents the normalization formula used to transform each indicator into a comparable scale before constructing the Human Capital Index.

Table 2: Normalization Formula of Human Capital Index

No	Indicators	Notation	Formula	Min	Max
Component 1: Survival					
1	Measles Immunization	MI	$\mathbf{MI_{it}} = \frac{\mathbf{x_{it} - 0\%}}{\mathbf{100\% - 0\%}}$	0%	100%
Component 2: School					
2	Expected Years of Schooling	EYS	$\mathbf{EYS_{it}} = \frac{\mathbf{x_{it} - 0}}{\mathbf{18 - 0}}$	0	18
3	Mean Years of Schooling	MYS	$\mathbf{MYS_{it}} = \frac{\mathbf{x_{it} - 0}}{\mathbf{15 - 0}}$	0	15
4	National Examination Score	NES	$\mathbf{NES_{it}} = \frac{\mathbf{x_{it} - 0}}{\mathbf{100 - 0}}$	0	100
Component 3: Health					
5	Life Expectancy	LE	$\mathbf{LE_{it}} = \frac{\mathbf{x_{it} - 20}}{\mathbf{85 - 20}}$	20	85

Source: Author’s Elaboration, 2026

After normalization, the HCI is constructed by first calculating the component scores. The survival component is represented by the normalized MI score, while the health component is represented by the normalized LE score. The schooling component is calculated as the average of the normalized EYS, MYS, and NES scores. The baseline HCI is then calculated using equal weights across the three components, as follows:

$$HCI_{it} = \frac{1}{3}Survival_{it} + \frac{1}{3}School_{it} + \frac{1}{3}Health_{it}$$

This weighting structure follows the multidimensional logic of the World Bank HCI framework, while adapting it to the available provincial-level data in Indonesia. The resulting HCI is expressed on a 0–100 scale, where higher values indicate better human capital performance.

To facilitate the interpretation of the Human Capital Index, this study classifies the HCI values into several categories using Sturges’ Rule. Sturges’ Rule is commonly used to

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determine the number of classes in grouped data and frequency distributions (Sturges, 1926; Scott, 2009), as expressed in the following formula:

$$k = 1 + 3.322\log_{10}(N)$$

where k is the number of classes and N is the number of provinces. Since this study covers 34 provinces, the number of classes is calculated as follows:

$$k = 1 + 3.322\log_{10}(34)$$
$$k = 1 + 3.322\ (1.5315)$$
$$k = 1 + 5.09$$
$$k = 6.09 \approx 6$$

Thus, the HCI values are classified into six categories: very low, low, moderately low, moderately high, high, and very high. After the number of classes is determined, the class interval is calculated using the empirical range of observed HCI values:

$$C = (b - a) / k$$

here C is the class interval, a is the minimum HCI value, b is the maximum HCI value, and k is the number of classes. This empirical classification is used because the adapted HCI does not have official normative thresholds at the provincial level. Therefore, the classification is intended to reflect the actual distribution of HCI values across Indonesian provinces during the study period.

Lastly, a robustness test is conducted to validate the calculation results of the Human Capital Index. The robustness test is based on the combination of high Pearson correlations and relatively small mean differences in index values under alternative weighting scenarios. Three alternative weighting schemes are developed by assigning greater weight to one component at a time: survival-emphasis, schooling-emphasis, and health-emphasis scenarios. In each scenario, the emphasized component receives 50% weight, while the remaining two components receive 25% each. The alternative HCI values are then compared with the baseline HCI using Pearson correlation, mean absolute difference, and mean percentage difference. This procedure is consistent with composite indicator guidelines, which emphasize the importance of testing whether index results are sensitive to methodological choices such as weighting and aggregation (OECD et al., 2008).

The analysis proceeds in three stages. First, descriptive statistics, heatmaps, and provincial rankings are used to describe the baseline HCI results. Second, spatial analysis is conducted using choropleth maps and Global Moran's I. Global Moran's I is used to examine whether the spatial distribution of average HCI and its normalized indicators exhibits spatial autocorrelation. Moran's I is a widely used measure for identifying whether similar values tend to be spatially clustered or randomly distributed across geographic units (Moran, 1950; Anselin, 1995). In this study, Moran's I is calculated using provincial average values for 2011–2019 and a contiguity-based spatial weight matrix. Third, temporal analysis is conducted by examining the trend of selected provinces, the annual mean, range, and standard deviation of HCI values. The range and standard deviation are used to assess whether interprovincial disparities in human capital became wider, narrower, or remained persistent during 2011–2019.

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4. Results and Discussion

4.1. Calculation Results of Human Capital Index

The Human Capital Index is calculated for Indonesian provinces during the 2011–2019 period. The index is expressed on a 0–100 scale, where higher values indicate better human capital performance. As shown in Table 3, the baseline HCI consists of 302 province-year observations. The mean HCI is 69.51, with a standard deviation of 3.39. The minimum value is 58.22, while the maximum value reaches 80.55, producing an overall range of 22.33 points. These descriptive statistics indicate that human capital performance varies across provinces and years, although most observations are concentrated around the middle range of the index.

Table 3: Descriptive Statistics of Human Capital Index

Statistic	Value
Observations	302
Mean	69.51
Standard Deviation	3.39
Minimum	58.22
Maximum	80.55
Range	22.33

Source: Author's Calculation, 2026

Furthermore, since HCI values are classified into six categories: very low, low, moderately low, moderately high, high, and very high, as calculated in Research Method section. Accordingly, the class interval is calculated using the range of the HCI values. The class interval is expressed as follows:

$$C = (b - a) / k$$

where C is the class interval, a is the minimum HCI value, b is the maximum HCI value, and k is the number of classes. Based on Table 3, the minimum value is 58.22 and the maximum value is 80.55. Therefore, the range (R) of the HCI is:

$$R = b - a$$
$$R = 80.55 - 58.22$$
$$R = 22.33$$

Thus, the class interval is calculated as follows:

$$C = \frac{b - a}{6} = \frac{80.55 - 58.22}{6} = 3.72$$

Table 4: Classification of Human Capital Index

Category	Interval
Very Low	58.22 ≤ HCI < 61.94
Low	61.94 ≤ HCI < 65.66
Moderately Low	65.66 ≤ HCI < 69.39
Moderately High	69.39 ≤ HCI < 73.11

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High	73.11 ≤ HCI < 76.83
Very High	76.83 ≤ HCI ≤ 80.55

Source: Author's Calculation, 2026

After establishing the classification intervals, the HCI values are visualized in the form of a heatmap to provide a clearer overview of the distribution of human capital across provinces and years. The heatmap in Table 5 uses the classification presented in Table 4, ranging from very low to very high, to show the spatial-temporal pattern of HCI values from 2011 to 2019. Based on Table 5, most province-year observations fall within the moderately low and moderately high categories, indicating that the level of human capital in Indonesia is generally concentrated in the middle range. However, clear spatial differences are observed. DI Yogyakarta consistently records very high HCI values, while DKI Jakarta, Bali, Kalimantan Timur, Sulawesi Utara, and Jawa Tengah tend to remain in the high or moderately high categories. In contrast, Papua consistently records the lowest HCI values, while Sulawesi Barat also remains among the lower-performing provinces. These patterns suggest that human capital development in Indonesia remains uneven across provinces.

To complement the heatmap, Table 6 presents the provincial ranking of average HCI and normalized indicator scores during 2011–2019. The table provides a clearer summary of overall human capital performance across provinces by ranking them from the highest to the lowest average HCI. In addition, the normalized indicator scores help identify which dimensions contribute to the relative position of each province. The results show that DI Yogyakarta records the highest average HCI, followed by DKI Jakarta, Kalimantan Timur, and Bali. These provinces generally show strong performance across several normalized indicators, particularly survival, schooling, and health-related components. In contrast, Papua records the lowest average HCI, followed by Sulawesi Barat and Kalimantan Barat. This ranking indicates that human capital development remains uneven across Indonesian provinces.

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Table 5: Calculation of Human Capital Index in Indonesia 2011 - 2019

No	Provinces	2011	2012	2013	2014	2015	2016	2017	2018	2019
1	ACEH	70.44	71.34	69.75	70.16	68.18	66.72	64.26	61.73	60.01
2	SUMATERA UTARA	68.21	69.50	69.43	70.28	68.07	68.96	68.31	66.49	66.10
3	SUMATERA BARAT	67.54	69.48	67.56	68.85	68.38	68.22	66.82	66.50	66.49
4	RIAU	70.08	70.20	69.55	71.10	70.06	69.99	68.77	66.72	66.14
5	JAMBI	70.16	70.89	69.52	69.72	69.89	69.89	68.24	68.10	68.40
6	SUMATERA SELATAN	69.66	71.04	69.71	70.11	70.79	69.88	68.74	67.58	66.83
7	BENGKULU	69.89	71.60	69.25	69.40	70.57	70.22	69.62	69.31	69.57
8	LAMPUNG	70.32	71.29	70.47	70.84	71.26	70.57	70.02	69.10	68.75
9	KEP. BANGKA BELITUNG	66.72	67.96	68.67	69.10	70.21	70.34	69.33	68.23	67.41
10	KEP. RIAU	71.90	72.26	72.35	71.19	73.27	72.83	70.51	71.01	71.93
11	DKI JAKARTA	73.75	75.46	73.81	75.32	76.13	74.43	74.36	74.08	74.14
12	JAWA BARAT	70.75	71.84	70.66	71.57	70.79	71.50	70.56	69.54	69.10
13	JAWA TENGAH	71.51	72.23	71.91	72.43	73.13	73.57	72.75	72.59	72.89
14	DI YOGYAKARTA	77.68	76.27	76.59	76.96	78.67	78.42	80.55	79.46	78.83
15	JAWA TIMUR	70.43	71.21	70.91	71.58	71.99	71.71	70.65	70.25	70.51
16	BANTEN	68.73	69.38	67.91	68.45	66.32	67.99	67.51	66.33	65.70
17	BALI	73.54	73.25	73.05	74.50	75.25	74.32	74.49	73.98	73.79
18	NUSA TENGGARA BARAT	67.89	69.53	68.58	69.93	69.87	70.06	68.55	67.79	68.08
19	NUSA TENGGARA TIMUR	67.38	67.62	67.22	68.01	67.85	69.03	68.45	68.00	68.11
20	KALIMANTAN BARAT	66.82	67.43	67.08	67.85	66.60	67.83	66.37	65.87	66.03
21	KALIMANTAN TENGAH	68.29	70.12	70.43	69.64	69.27	68.79	68.13	67.45	67.12
22	KALIMANTAN SELATAN	66.68	68.77	67.51	67.95	68.90	68.84	68.25	67.62	67.46
23	KALIMANTAN TIMUR	73.71	74.90	74.79	74.22	73.99	75.48	73.14	72.92	73.02
24	KALIMANTAN UTARA					71.12	72.13	71.30	71.19	71.16
25	SULAWESI UTARA	71.91	73.02	72.71	73.02	74.15	73.72	72.33	71.29	71.32
26	SULAWESI TENGAH	65.96	67.13	66.87	68.34	67.33	68.34	67.43	66.88	67.04
27	SULAWESI SELATAN	69.38	70.93	69.46	70.59	71.12	70.82	69.98	68.92	68.88
28	SULAWESI TENGGARA	69.68	70.92	70.60	71.76	71.37	71.90	70.99	70.72	70.79
29	GORONTALO	68.87	68.44	67.96	68.53	69.23	70.06	69.43	68.39	68.40

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30	SULAWESI BARAT	62.40	64.73	64.25	64.18	65.05	66.05	64.69	64.37	64.42
31	MALUKU	66.64	67.99	67.93	68.63	68.41	68.35	67.96	67.62	67.42
32	MALUKU UTARA	68.84	70.44	69.76	70.97	67.29	69.63	68.23	67.17	66.35
33	PAPUA BARAT	66.61	67.79	67.52	68.43	67.00	69.62	65.83	65.47	66.02
34	PAPUA	58.22	60.17	60.26	60.42	59.73	58.98	59.79	59.65	59.43

Very High
High
Moderately High
Moderately Low
Low
Very Low

Source: Author's Calculation, 2026

Table 6: Provincial Ranking of Average HCI and Indicator Scores, 2011–2019

Rank	Provinces	MI	EYS	MYS	NES	LE	HCI	Category
1	DI YOGYAKARTA	82.08	83.70	63.44	58.02	84.01	**78.16**	Very High
2	DKI JAKARTA	76.52	69.50	73.21	57.53	80.56	**74.61**	High
3	KALIMANTAN TIMUR	77.41	72.79	63.30	50.29	82.52	**74.02**	High
4	BALI	81.49	71.07	58.48	55.27	78.96	**74.02**	High
5	SULAWESI UTARA	78.20	68.12	61.62	53.77	78.45	**72.61**	Moderately High
6	JAWA TENGAH	78.14	67.49	50.76	52.32	82.67	**72.56**	Moderately High
7	KEP. RIAU	77.76	69.14	66.09	51.34	75.81	**71.92**	Moderately High
8	KALIMANTAN UTARA	72.63	70.64	60.27	51.67	80.65	**71.38**	Moderately High
9	JAWA TIMUR	76.27	69.73	51.36	55.82	77.83	**71.03**	Moderately High
10	SULAWESI TENGGARA	74.39	72.06	58.00	52.88	77.55	**70.97**	Moderately High
11	JAWA BARAT	73.51	66.57	55.59	52.33	80.43	**70.70**	Moderately High
12	LAMPUNG	76.98	67.19	53.69	50.99	76.61	**70.29**	Moderately High
13	SULAWESI SELATAN	73.67	71.31	54.89	53.41	76.49	**70.01**	Moderately High
14	BENGKULU	75.92	72.33	58.14	47.36	74.62	**69.94**	Moderately High

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15	JAMBI	71.40	69.06	56.37	51.87	77.78	**69.42**	Moderately High
16	SUMATERA SELATAN	74.78	66.17	54.88	52.56	75.47	**69.37**	Moderately Low
17	RIAU	67.98	69.86	59.46	54.57	78.26	**69.18**	Moderately Low
18	NUSA TENGGARA BARAT	79.83	71.59	49.71	50.87	69.53	**68.92**	Moderately Low
19	GORONTALO	76.90	69.60	51.12	50.44	72.49	**68.81**	Moderately Low
20	KALIMANTAN TENGAH	71.92	66.75	56.05	52.49	76.06	**68.80**	Moderately Low
21	MALUKU UTARA	71.80	71.94	59.27	53.10	72.98	**68.74**	Moderately Low
22	KEP. BANGKA BELITUNG	74.75	63.32	52.86	47.50	76.68	**68.66**	Moderately Low
23	SUMATERA UTARA	67.83	70.39	62.23	56.69	74.18	**68.37**	Moderately Low
24	KALIMANTAN SELATAN	72.20	66.85	54.43	53.97	73.38	**68.00**	Moderately Low
25	NUSA TENGGARA TIMUR	77.28	69.96	49.50	48.00	70.79	**67.96**	Moderately Low
26	MALUKU	69.89	75.15	63.20	54.31	69.54	**67.88**	Moderately Low
27	SUMATERA BARAT	66.67	74.85	59.04	51.92	74.67	**67.76**	Moderately Low
28	BANTEN	68.56	68.59	58.26	48.32	75.82	**67.59**	Moderately Low
29	SULAWESI TENGAH	70.32	70.33	56.25	49.74	72.68	**67.26**	Moderately Low
30	PAPUA BARAT	70.85	66.81	61.19	55.00	69.58	**67.14**	Moderately Low
31	ACEH	62.00	76.19	61.61	50.57	76.08	**66.96**	Moderately Low
32	KALIMANTAN BARAT	69.03	66.45	49.19	49.10	76.68	**66.87**	Moderately Low
33	SULAWESI BARAT	70.19	66.65	50.73	49.40	67.60	**64.46**	Low
34	PAPUA	59.38	55.65	44.33	50.83	69.23	**59.63**	Very Low

Source: Author’s Calculation, 2026

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4.2. Robustness Test of Human Capital Index

The robustness test confirms that the proposed Human Capital Index in Indonesia is stable under alternative weighting scenarios. As shown in Table 7, all alternative scenarios produce very high Pearson correlation coefficients with the baseline HCI. The correlation coefficients are 0.9545 for the survival-emphasis scenario, 0.9568 for the school-emphasis scenario, and 0.9781 for the health-emphasis scenario. All coefficients are statistically significant at the 1% level. This indicates that the alternative weighting schemes preserve a very strong linear relationship with the baseline index.

Table 7. Robustness Test of Human Capital Index

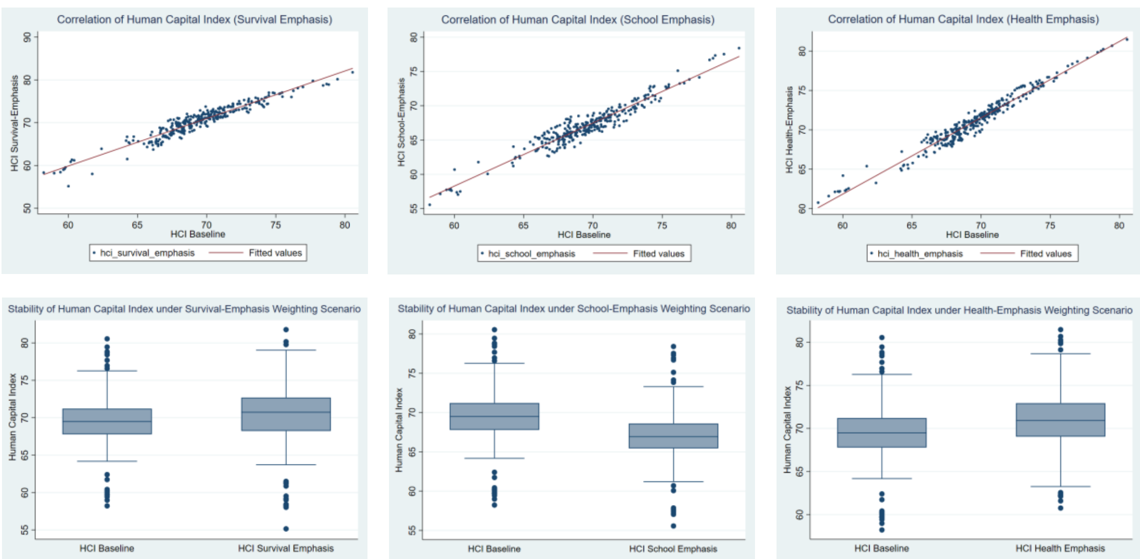
Scenario	Pearson	Mean Abs Diff	Mean % Diff	Conclusion
Survival-emphasis	0.9545***	1.27	1.83%	Robust
School-emphasis	0.9568***	2.48	3.56%	Robust
Health-emphasis	0.9781***	1.55	2.25%	Robust

Source: Author's Calculation, 2026

Note: The robustness test is based on pooled province-year observations for 2011–2019 (N = 302). All HCI values are normalized on a 0–100 scale. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Furthermore, the magnitude of the differences is also relatively small. The mean absolute difference is 1.27 points for the survival-emphasis scenario, 2.48 points for the school-emphasis scenario, and 1.55 points for the health-emphasis scenario. Similarly, the mean percentage difference is 1.83%, 3.56%, and 2.25%, respectively. These values suggest that changing the component weights does not substantially alter the final HCI scores. Although the largest average change occurs in the school-emphasis scenario, the difference remains modest at only 3.56%, it supports the robustness.

Figure 1: Robustness Test Visualization of Human Capital Index



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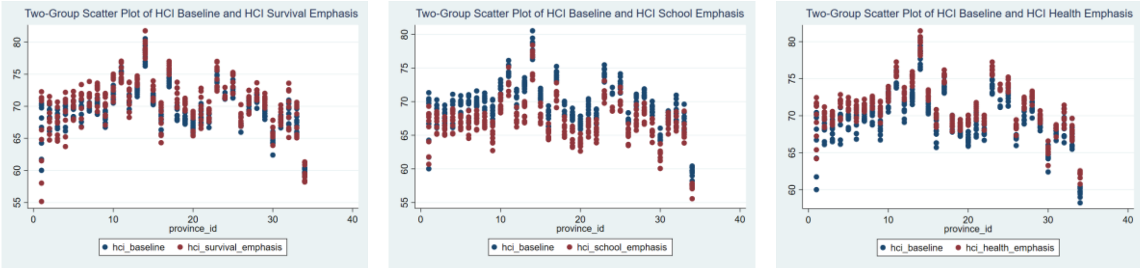


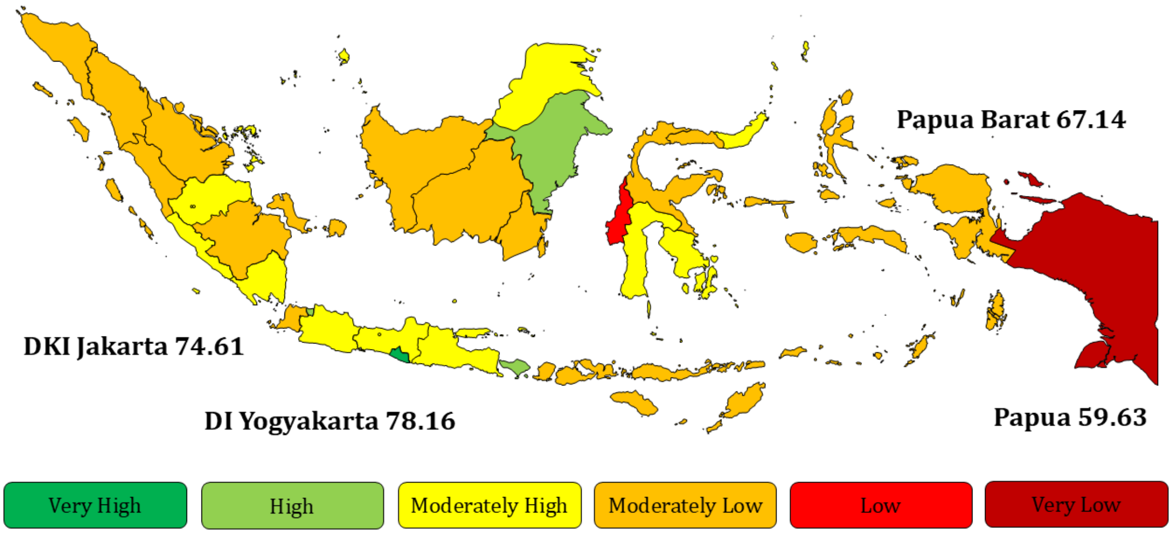
Source: Author's Calculation, 2026

Moreover, Figure 1 further supports the robustness test. The correlation plots show that the observations are closely clustered around the fitted lines across the survival-, school-, and health-emphasis scenarios. The boxplots indicate that the distribution of HCI scores under alternative weighting schemes remains broadly comparable to the baseline distribution. In addition, the two-group scatter plots show that the alternative HCI values move closely with the baseline values across province-year observations. Overall, the results indicate that the proposed Human Capital Index is robust to changes in weighting assumptions. Although minor shifts in index values occur, the high correlations and small average differences confirm that the overall structure and interpretation of the index remain stable across alternative weighting scenarios.

4.3. Spatial Patterns of Human Capital Index across Indonesia's Provinces

This section examines the spatial distribution of human capital across Indonesia's provinces using the average HCI during 2011–2019. Subnational human capital assessment is important because national-level averages may conceal substantial territorial differences in education, health, and broader development outcomes. Similar regional human capital studies have used composite indices and GIS-based mapping to identify spatial differentiation and support regional policy interpretation (Duisen et al., 2025).

Figure 2. Spatial Distribution of Average Human Capital Index across Indonesia's Provinces, 2011–2019



Source: Author's Calculation & Author's Illustration, 2026

Figure 2 shows that the spatial distribution of HCI is uneven across Indonesian provinces. Higher HCI values are observed in DI Yogyakarta, DKI Jakarta, Kalimantan

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Timur, and Bali, while lower values are concentrated in Papua and Sulawesi Barat. Several provinces fall within the moderately low and moderately high categories, indicating that most provinces are clustered around the middle range of human capital performance.

To complement the visual interpretation of the map, Global Moran's I is used to examine whether the spatial distribution of average HCI and its normalized indicators exhibits spatial autocorrelation. This test identifies whether provinces with similar HCI or indicator values tend to be geographically clustered or whether the observed spatial pattern is more randomly distributed. Table 8 shows that the Moran's I value for HCI is positive but not statistically significant (I = 0.051; p = 0.116). This indicates that the average HCI across Indonesian provinces does not form a strong global spatial clustering pattern. In other words, high-HCI and low-HCI provinces are not systematically concentrated in neighboring areas. This finding is plausible in the Indonesian context, given the archipelagic geography and the dispersed location of high-performing provinces, such as DI Yogyakarta, DKI Jakarta, Bali, Kalimantan Timur.

Table 8: Global Moran's I Test for Average HCI and Normalized Indicators

Variables	**Moran's I**	**z-value**	**p-value**	**Interpretation**
HCI	0.051	1.194	0.116	Not significant
MI	0.129**	2.267	0.012	Positive spatial autocorrelation
EYS	-0.048	-0.264	0.396	Not significant
MYS	-0.058	-0.399	0.345	Not significant
NES	0.023	0.746	0.228	Not significant
LE	0.152***	2.565	0.005	Positive spatial autocorrelation

Source: Author's Calculation, 2026

Note: N = 34 provinces. Moran's I was calculated using a distance-based binary spatial weight matrix. HCI and all indicators are based on provincial average values for 2011–2019 and normalized on a 0–100 scale. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

However, the results show a different pattern for health and survival-related indicators. Measles Immunization has a positive and statistically significant Moran's I value (I = 0.129; p = 0.012), while Life Expectancy also shows positive and statistically significant spatial autocorrelation (I = 0.152; p = 0.005). These findings suggest that health and survival-related indicators tend to be spatially clustered across provinces. In contrast, education-related indicators, including Expected Years of Schooling, Mean Years of Schooling, and National Examination Score, do not show statistically significant global spatial autocorrelation.

The Moran's I result indicate that while the composite HCI itself does not exhibit significant global spatial clustering, some of its underlying survival and health-related indicators do. This suggests that provincial differences in human capital are spatially uneven, but the composite index captures multidimensional variation that is not solely determined by geographic proximity. The significant spatial clustering of Measles Immunization and Life Expectancy further indicates that health-related dimensions may have stronger geographical patterns than education-related indicators.

To provide a clearer visual comparison of these underlying patterns, Figure 3 presents the spatial distribution of each normalized HCI indicator, namely Measles Immunization, Expected Years of Schooling, Mean Years of Schooling, National Examination Score, and

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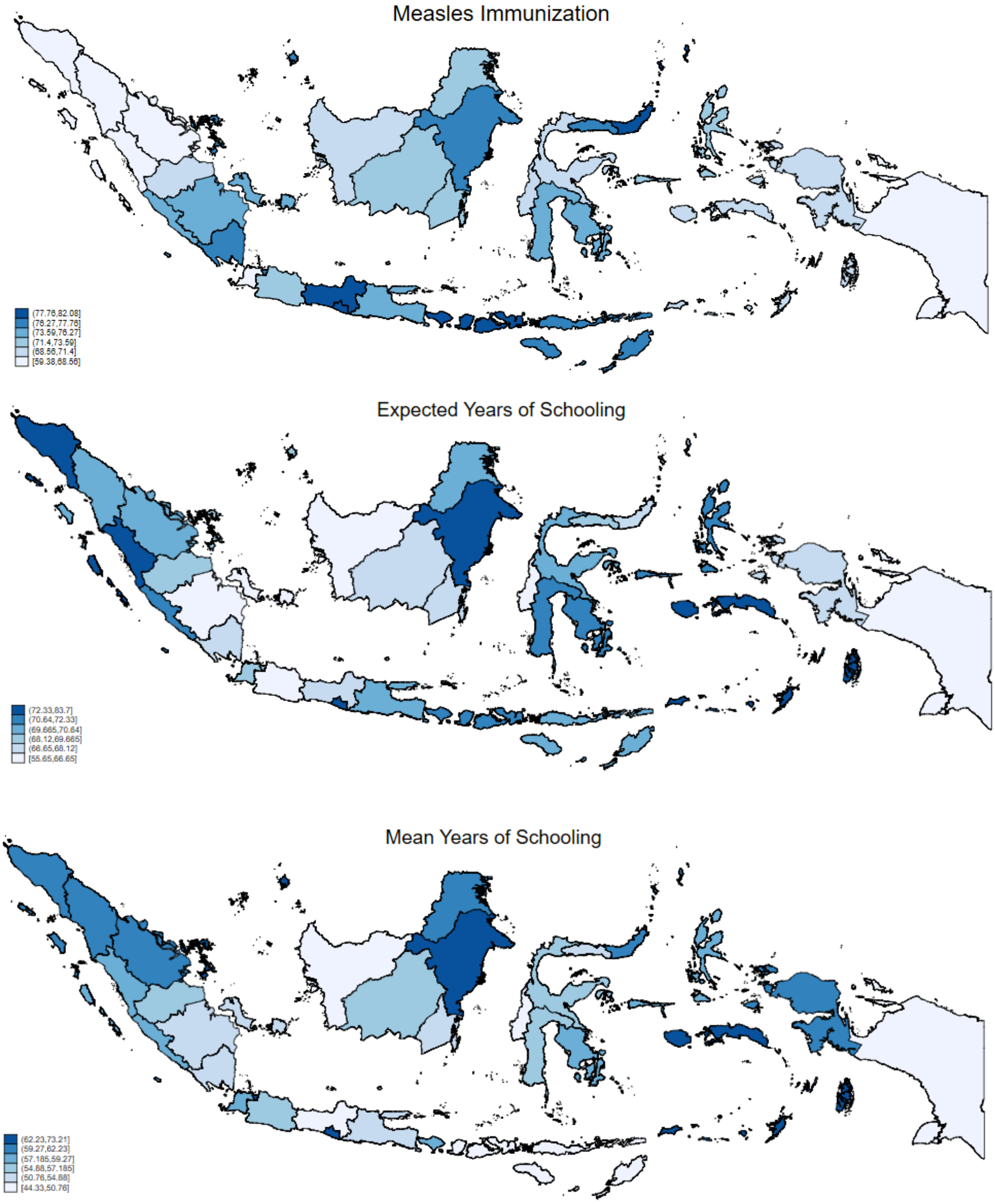
Life Expectancy. These indicator maps illustrate whether the spatial patterns observed in the composite HCI are also reflected in its individual dimensions.

Figure 3: Spatial Distribution of the HCI's Indicators



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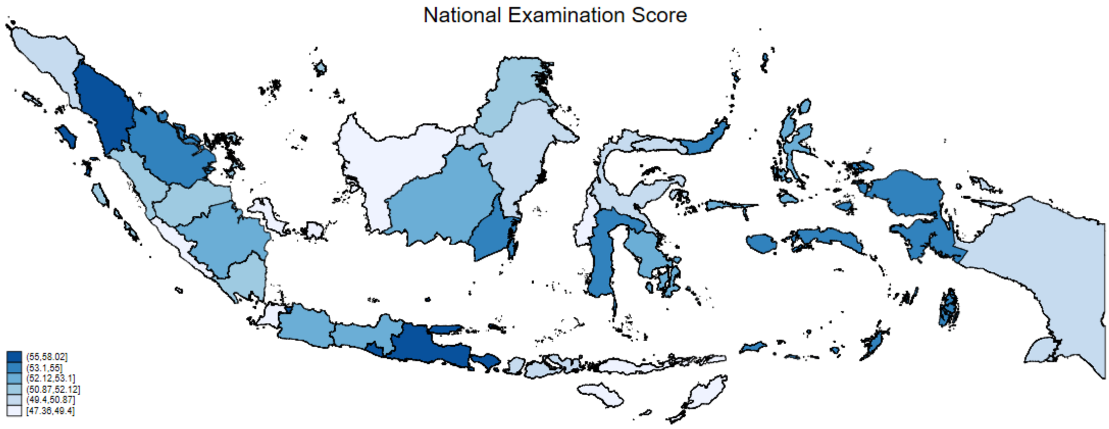

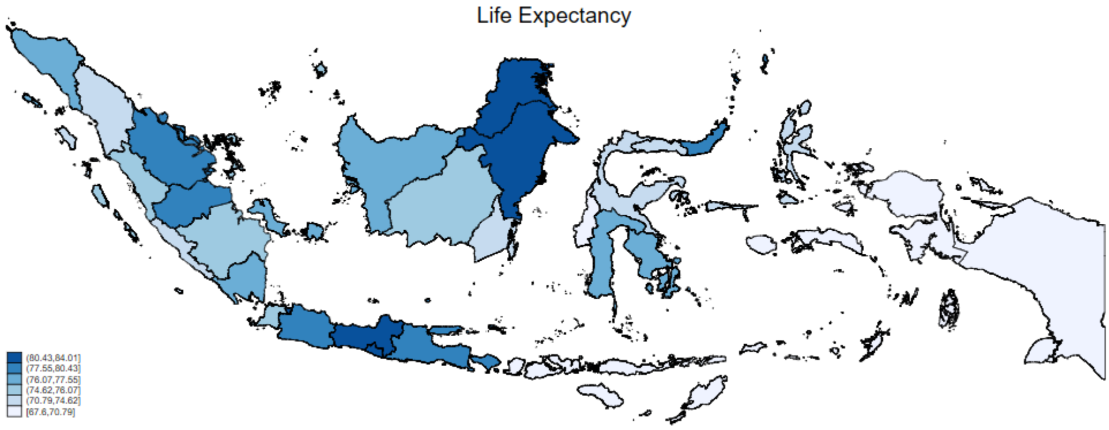

Source: Author's Calculation & Author's Illustration, 2026

The indicator maps show that the spatial patterns of HCI components are not uniform. Measles Immunization and Life Expectancy display clearer geographical concentration, which is consistent with their positive and statistically significant Moran's I values. In contrast, Expected Years of Schooling, Mean Years of Schooling, and National Examination Score appear more spatially dispersed, supporting the insignificant Moran's I results for education-related indicators. This reinforces the finding that health and survival-related dimensions have stronger spatial patterns than education-related dimensions in explaining provincial human capital differences.

To further interpret the spatial variation in provincial HCI, a Pearson correlation analysis is conducted between average HCI and its normalized indicators. This analysis identifies which indicators are most closely associated with differences in average HCI across provinces. Table 9 presents the Pearson correlation matrix between average HCI and normalized indicators for 34 provinces during 2011–2019.

The results show that all indicators are positively associated with average HCI, indicating that higher values in survival, education, and health-related indicators tend to correspond with higher provincial HCI performance. This finding is consistent with the multidimensional logic of the World Bank HCI framework, which combines survival, schooling, and health-related dimensions to represent human capital and productivity (Kraay, 2018, 2019). Among the indicators, Life Expectancy and Measles Immunization show the strongest correlations with HCI, with coefficients of 0.7939 and 0.7915, respectively. This suggests that provincial differences in HCI are most closely associated with health and survival-related dimensions. Provinces with better life expectancy and immunization performance tend to achieve higher overall human capital scores.

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Table 9: Pearson Correlation of Average HCI and Normalized Indicators, 2011–2019

	HCI	**MI**	**EYS**	**MYS**	**NES**	**LE**
HCI	1					
MI	0.7915***	1				
EYS	0.5780***	0.3040*	1			
MYS	0.5623***	0.1363	0.5277***	1		
NES	0.4648***	0.1731	0.3142*	0.4936***	1	
LE	0.7939***	0.4099**	0.3033*	0.3828**	0.3097*	1

Source: Author's Calculation, 2026
Note: N = 34 provinces. All indicators are normalized on a 0–100 scale. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Education-related indicators also show positive and statistically significant associations with HCI. Expected Years of Schooling and Mean Years of Schooling have moderate correlations with HCI, at 0.5780 and 0.5623, respectively. Meanwhile, the National Examination Score records a lower but still statistically significant correlation of 0.4648. These results indicate that schooling indicators remain important in explaining provincial HCI differences, although their associations are relatively weaker than those of health and survival indicators. This suggests that educational access, attainment, and learning outcomes are relevant to provincial human capital performance, but the overall variation in HCI across provinces is more strongly aligned with health-related conditions.

The correlations among education indicators also provide additional insight. Expected Years of Schooling is positively correlated with Mean Years of Schooling, while Mean Years of Schooling is also significantly associated with the National Examination Score. This indicates that provinces with longer schooling duration tend to show better educational performance. However, the correlations are not excessively high, suggesting that each indicator captures a different aspect of human capital formation.

Lastly, the correlation results indicate that provincial HCI performance is not aligned with a single indicator alone, but reflects the combined role of survival, schooling, and health dimensions. Life Expectancy and Measles Immunization appear to be the indicators most closely associated with differences in average HCI across Indonesian provinces. The strong association between Life Expectancy and HCI is consistent with recent evidence that subnational life expectancy disparities are an important dimension of within-country health and development inequalities in low- and middle-income countries (Kyriacou et al., 2025).

Overall, the spatial analysis indicates that human capital development in Indonesia remains uneven across provinces. The choropleth map shows clear provincial variation, while Global Moran's I indicate that the composite HCI does not form a significant global spatial cluster. However, the significant Moran's I value for Measles Immunization and Life Expectancy, combined with their strong correlations with HCI, suggest that health and survival-related indicators play an important role in explaining provincial differences in human capital performance. This reinforces the argument that human capital should be interpreted as a multidimensional construct rather than through a single schooling-based indicator alone (Kraay, 2019).

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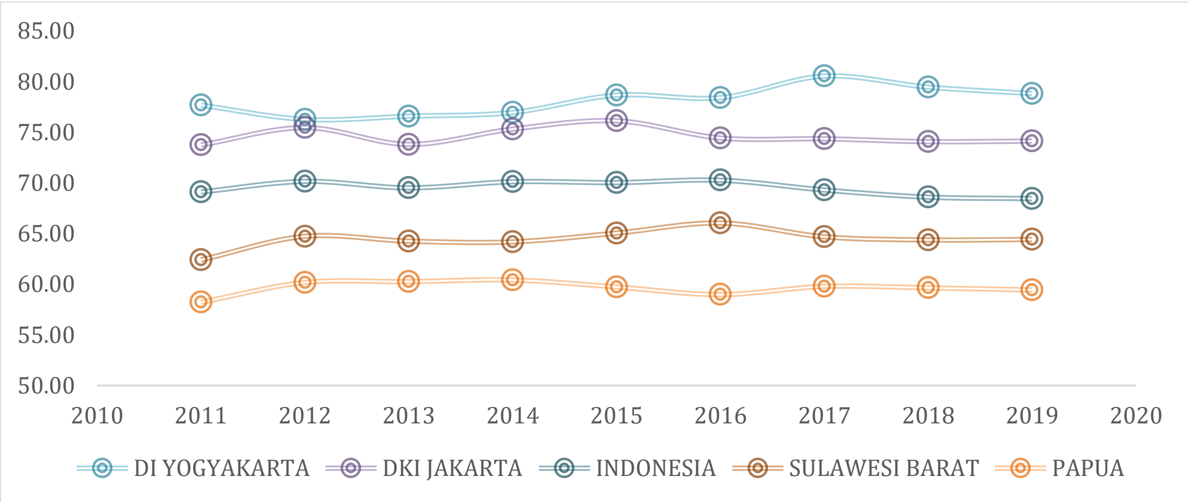
4.4. Temporal Patterns of Human Capital Index, 2011 - 2019

After discussing the spatial distribution of HCI across provinces, this section analyzes the temporal pattern of human capital during 2011–2019. The temporal analysis focuses on two main aspects: changes in the average HCI over time and the evolution of interprovincial disparities. The annual mean HCI is used to assess the overall trajectory of human capital performance, while the range and standard deviation are used to examine whether differences across provinces became wider, narrower, or remained persistent during the observation period.

Figure 4. Temporal Trend of HCI in Selected Provinces and Indonesia, 2011–2019



Source: Author's Calculation & Author's Illustration, 2026

Figure 4 shows the temporal trend of HCI in selected provinces and Indonesia during 2011–2019. Overall, the figure indicates that HCI values remained relatively stable over time, with no substantial year-to-year changes. DI Yogyakarta consistently recorded the highest HCI, followed by DKI Jakarta, while Papua and Sulawesi Barat remained below the Indonesian average throughout the period. The Indonesian average also shows a relatively stable pattern, suggesting that overall human capital performance did not change dramatically during the observation period. More importantly, the relative positions of high- and low-performing provinces remained largely unchanged, indicating persistent interprovincial disparities in human capital.

To further assess whether interprovincial disparities in human capital narrowed or persisted over time, the temporal pattern of dispersion is examined using the annual range and standard deviation of HCI across provinces. While the previous figure illustrates the movement of HCI levels in selected provinces, these dispersion measures provide a broader picture of whether inequality in human capital performance became smaller or remained stable during 2011–2019.

Figure 5 shows the temporal evolution of interprovincial disparities in HCI using the annual range and standard deviation. The results indicate that both measures fluctuated during 2011–2019, but neither shows a clear downward trend. The range declined from 19.46 in 2011 to 16.10 in 2012, but it increased again in the following years and remained relatively wide until 2019. Similarly, the standard deviation decreased slightly in the early period, but increased toward the end of the observation period, reaching 3.756 in 2019.

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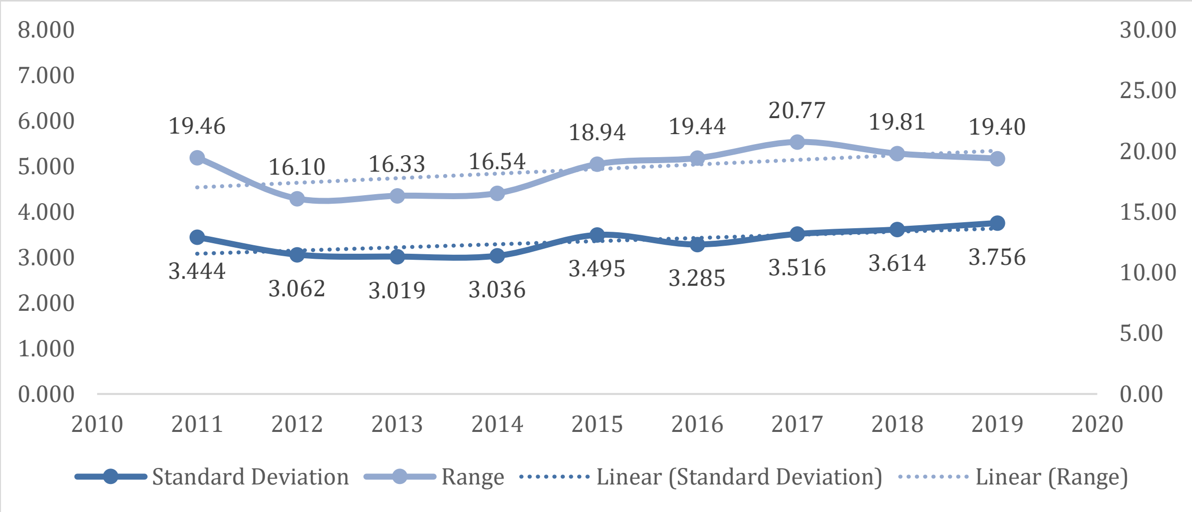
Figure 5: Trend of HCI Range and Standard Deviation, 2011–2019



Source: Author's Calculation & Author's Illustration, 2026

The trend lines further suggest that interprovincial disparities did not substantially narrow over time. In particular, the upward tendency in the standard deviation indicates that the dispersion of HCI values across provinces remained persistent and even became slightly wider in the later years. This means that although HCI values may have changed slightly from year to year, the overall gap between higher-performing and lower-performing provinces did not show meaningful convergence.

Overall, the temporal analysis indicates that human capital development in Indonesia was characterized by persistence rather than rapid convergence during 2011–2019. Provinces with higher HCI values generally maintained their relative advantage, while provinces with lower HCI values continued to lag behind. This finding strengthens the spatial analysis by showing that provincial disparities in human capital were not only visible across regions, but also persisted over time. This finding is consistent with regional human capital studies showing that composite human capital performance may improve or fluctuate over time while interregional disparities remain persistent (Duisen et al., 2025).

5. Conclusion, Policy Recommendation, Limitations, and Future Research

This study develops Human Capital Index for Indonesian provinces based on the World Bank HCI framework using normalized indicators of survival, schooling, and health. The results show that the proposed HCI provides a useful measure for comparing human capital performance across provinces during 2011–2019. The index is also robust under alternative weighting scenarios, as shown by the high correlations and small average differences between the baseline and alternative HCI calculations.

The findings indicate that human capital development in Indonesia remains uneven across provinces. DI Yogyakarta, DKI Jakarta, Kalimantan Timur, and Bali consistently record higher HCI values, while Papua and Sulawesi Barat remain among the lowest-performing provinces. The spatial analysis shows that the composite HCI does not form a significant global spatial cluster, but health and survival-related indicators, particularly Measles Immunization and Life Expectancy, show significant spatial autocorrelation. The

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correlation also indicate that these two indicators are most closely associated with provincial HCI differences. Meanwhile, the temporal analysis shows that interprovincial disparities persisted during 2011–2019, with no clear evidence of convergence between high- and low-performing provinces.

From a policy perspective, these findings suggest that human capital policies in Indonesia should be more territorially targeted and indicator-specific. Provinces with persistently low HCI, such as Papua and Sulawesi Barat, require priority intervention through integrated health, education, and social protection programs. Since Measles Immunization and Life Expectancy are strongly associated with provincial HCI differences, local governments should strengthen basic health services by expanding immunization coverage, improving maternal and child health services, increasing access to primary healthcare facilities, and ensuring the availability of health workers in underserved areas. Nutrition programs should also be prioritized, particularly through early childhood health monitoring, school-based nutrition initiatives, and community health posts.

In the education sector, policy should not focus only on increasing years of schooling, but also on improving learning quality. Provinces with weak schooling indicators need targeted support through teacher quality improvement, remedial learning programs, school infrastructure improvement, and stronger monitoring of learning outcomes. This HCI can be used as a provincial diagnostic tool to identify which dimensions require intervention in each region. Therefore, national and regional governments should regularly update provincial HCI scores and integrate them into regional development planning, budget allocation, and monitoring of human capital programs.

While the findings provide important insights for provincial human capital policy, this study also recognizes several limitations. These limitations do not undermine the usefulness of the adapted HCI, but they should be considered when interpreting the results, particularly because the construction of the index depends on the availability and consistency of provincial-level data. First, the index cannot fully adopt all original indicators from the World Bank HCI framework because consistent provincial-level data are not available for Indonesia during 2011–2019. Therefore, this study uses theoretically relevant proxies, such as Measles Immunization as a survival-related indicator. Second, stunting cannot be included because consistent annual provincial data are not available for the full period. Third, the National Examination Score is used for measure learning outcomes, but this indicator is limited because the national examination was discontinued after 2020. As a result, the index is restricted to the 2011–2019 period.

Future research can extend this study by using the HCI as an independent variable in empirical models of economic growth in Indonesia. Since this study provides a more comprehensive measure of human capital than single indicators such as Mean Years of Schooling or Expected Years of Schooling, the index can be used to examine how human capital contributes to growth. Future studies may also update the index when more complete data become available, especially data on child survival, stunting, and learning outcomes, so that the World Bank HCI framework can be more fully adapted to the Indonesian context.

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Ethics Approval and Consent to Participate

The study adhered to the ethical guidelines established by the Research Ethics Committee of the International Islamic University Malaysia (IIUM).

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Conflict of Interest

The authors declared that they had no conflicts of interest related to this study and confirmed that no potential conflicts existed concerning the research, authorship, or publication of the article.

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