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REVIEW ARTICLE

Human Capital and Regional Economic Growth in Indonesia: A Spatial Analysis Approach

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Abstract Endogenous growth theory assumes that human capital is a prominent factor in regional economic growth. However, the imbalance of human capital between regions is still a major problem in economic growth in Indonesia. Previous studies on regional economic growth have recognized the importance of considering spatial aspects as a determinant of regional economic growth. The geographical area in the form of an archipelago with a large number of administrative districts and cities produces pros and cons regarding the influence of spatial aspects on the regional growth of urban districts. This study aims to analyze the distribution of human capital using the Alternative Human Development Index (AHDI) approach and the effect of human capital and spatial aspects on the regional economic growth of urban districts in Indonesia within the framework of endogenous growth theory. The research method uses geometric mean to measure the Alternative Human Development Index, Geographic Information System (GIS) to see the distribution of human capital and regional economic growth in Indonesia, and the spatial regression Spatial Autoregressive Moving Average (SARMA) used to analyze the spatial aspects of human capital and regional economic growth in Indonesia. The results show that human capital in Indonesia is still unequal between the western and eastern parts of Indonesia. Human capital and spatial factors have positive effects and are the most influential determinants of Indonesia's regional economic growth, as indicated by the value of the spatial lag weight matrix of the dependent variable (ρ) and the spatial error term (λ) that is positive.

1. Introduction

In Indonesia, regional disparities in terms of territory, population, the availability of natural resources, and cultural distinctions continue to be the primary obstacle to development, including variations in human capital (Adam & Negara, 2015; Yulianita et al., 2017; Wicaksono et al., 2017; Akita & Miyata, 2018; Lee & Lee, 2018; Anwar, 2018; Affandi et al., 2019; Ragdad Cani & Mendez, 2020), and differences in premium wage rates (Mulyaningsih et al., 2019). These differences, however, have made the analysis of regional development patterns interesting because they relate to development policies. One of the policy analyses that can be carried out is to find out the main factors that drive regional economic progress, using regional economic growth regressions (Adam & Negara, 2015; Dewanta et al., 2017; Affandi et al., 2019; Agusalim et al., 2022). Human capital is a key component of regional economic growth, according to the endogenous growth theory (Romer, 1990; Lucas, 1988). However, disparities in human capital also lead to differences in the rate of development between regions; regions with higher economic levels typically have higher levels of human capital (Tamura et al., 2019; Kokuytseva & Ovchinnikova, 2020).

Several studies use the Human Development Index (HDI) as a surrogate for human capital when measuring human capital (Ragdad Cani & Mendez, 2020; Ridha & Budi, 2020; Liu et al., 2023). The HDI has been regarded as a comprehensive indicator of human capital for many years due to its utilization of numerous factors, including longevity, education, and economic factors. However, several recent studies state that HDI has several weaknesses, as it does not include human capital dimension and does not consider other dimensions beyond economic, education and longevity dimensions either. HDI modification is therefore needed to improve the size of human capital by adding dimensions of human capital (Bourgoin, 2014; Amaluddin et al., 2018; Leiwakabessy & Amaluddin, 2020; Windhani et al., 2022). With regard to spatial aspect, neighboring areas will have a pattern of spatial linkages, where the economic performance of a region will affect its neighboring regions (Vidyattama, 2013; Márquez et al., 2019). One of the biggest archipelagic nations, Indonesia has a sizable population and extensive territory. The borders between regions, which are primarily water boundaries, are influenced by the shape of an archipelagic state. Territory boundaries in the form of waters are one of the obstacles to interaction between regions (Rizaldi et al., 2023). However, in the study of Márquez et al., (2019), it was stated that smaller areas have greater interactions, thereby reducing inequality between regions. Spatial effects will occur more at the level of smaller areas such as regencies and municipalities.

Regression analysis to analyze regional economic performance is not sufficient to explain the determinants of economic growth. To comprehensively identify the determinants of economic growth across different regions, it is crucial to incorporate the consideration of spatial impacts. Based on geographic location, the spatial component examines the connection between the economic performance of specific regions and their surroundings (Elhorst, 2014). The region itself will be impacted by the spatial relationships that exist between nearby regions (spatial autocorrelation). The phenomenon of economic growth between regions can be more accurately described by number of studies on economic growth that make use of spatial analysis. According to Anwar (2017), spatial analysis reveals that economic growth in Indonesia is still uneven across regions, with urban areas like Jakarta, Surabaya, and Yogyakarta dominating the center of economic growth and human capital. According to a study by Ragdad Cani & Mendez (2020), spatial factors can accelerate the convergence of human capital, resulting in a faster decline in regional inequality and more equitable economic growth. According to a different study by Utami et al. (2022), a region's economic growth will accelerate when spatial aspects are utilized. Nevertheless, different findings from research by Aritenang & Chandramidi (2023) indicated that using spatial aspects does not effectively lessen regional differences in economic growth.

This study makes two primary contributions: first, it applies the Alternative Human Development Index (AHDI) approach developed by Windhani et al. (2022) to the measuring of human capital. Secondly, employing geographical dimensions within the framework of endogenous growth theory to elucidate the impact of human capital on economic growth among Indonesian regions. The regional growth model is modified in a number of recent studies that look at regional economic growth by adding spatial components (Vidyattama, 2014; Xu & Li, 2020; Aspiansyah & Damayanti, 2019). Using data at the province level research of Vidyattama (2008), Vidyattama (2014), Anwar (2017), Aspiansyah & Damayanti (2019), and Xu & Li (2020) carried out a number of studies on regional growth in Indonesia that took spatial features into account. The outcomes demonstrated that the spatially-aspectual regional growth model produced distinct outcomes from the conventional regional growth model. The distribution of human capital and regional economic growth in Indonesia are the primary objectives of this study. Second, using the endogenous economic development theory as a theoretical framework, examine how human capital and spatial factors affect Indonesia's regional economic growth.

This paper is organized into four parts. The first part discusses the introduction of research. The second part describes the research method, consisting of geometric mean, Geographic Information Systems (GIS) and spatial regression of panel data. The third part discusses the results of research and discussion. The last part is the conclusion of the research.

2. Methods

Measuring Human Capital with the Use of Alternative Human Development Index (AHDI) Approach

With the addition of a human capital component to its measurement, the HDI modification was created to enhance. Study of Windhani et al. (2022) the elements of female empowerment, democracy, and health quality were included in the modified HDI. Each component of the measurement, which employs a geometric average, adds to the total amount of human capital. human capital is calculated using standardized values, with values falling between 0 and 1. The following formula is used for standardized values (Bourgoin, 2014):

$$Standardized\ value = \frac{actual\ value - minimum\ value}{maximum\ value - minimum\ value} \quad (1)$$

HDI measurements can be written in the following equation (Liu et al., 2023):

$$HDI = \sqrt[3]{Education \times Economic \times Longevity} \quad (2)$$

where Education is the education index, which includes both the expected and average years of education; Economic is an adjusted spending per capita index; The index of longevity is life expectancy.

The following equation represents changes to the AHDI approach's human capital measurement based on HDI measurements (Windhani et al., 2022):

$$AHDI = \sqrt[6]{Education \times Economic \times Longevity \times Gender \times Democracy \times Health} \quad (3)$$

Where *Gender* is gender empowerment index; *Democracy* is democracy index; and *Quality of Health* is quality of health.

Regional Economic Growth Models and Spatial Effects Empirical Model of Regional Economic Growth

According to the endogenous growth model, the rate of economic growth varies throughout regions based on how strong the local economy is. Human capital is highlighted as the primary driver of regional economic growth in endogenous growth theory (Romer 1990). The endogenous theory predicts that increases in human capital will result in higher rates of return. Additionally, it has a stronger impact on local economic expansion (Bucci & Segre, 2011; Trimborn, 2018). Human capital was included in the estimation of the model created by Bucci & Segre (2011) and Trimborn (2018), and it is expressed in the following equation:

$$Y_t = \alpha_{it} K_{it}^{\beta} L_{it}^{\gamma} H_{it}^{\omega} u_{it} \quad (4)$$

Where Y_t is regional economic growth; α_{it} is the level of technology; K_{it}^{β} is physical capital; L_{it}^{γ} is labor; H_{it}^{ω} is human capital; and u_{it} is the error term.

To determine the true drivers of growth, it is crucial to empirically incorporate additional regional economic growth variables into the regional economic growth model. In addition, the model's inclusion of economic growth factors lessens the bias caused by missing variables. The inconsistent estimation of the coefficients caused by eliminating the independent variables that have an impact on the dependent variable is known as the omitted variable bias (Gujarati, 2004). By including spatial and temporal impacts, the panel model estimate approach reduces variable bias and captures any unobservable properties of each economic unit (Chen & Gupta, 2006; Teixeira & Queirós, 2016; Sharma, 2018):

$$Y_t = \alpha_{it} K_{it}^{\alpha} L_{it}^{\beta} H_{it}^{\gamma} u_{it} \delta_t T_t' \eta_i \quad (5)$$

$$Y_{it} = \alpha_{it} + \beta K_{it} + \gamma L_{it} + \omega H_{it} + \delta_t T_t' + \eta_i + u_{it} \quad (6)$$

Where T_t' is the time effect variable vector and η_i is the regional fixed effect variable. However, specifications with panel data models cannot include spatial effects, which may have a significant influence on both regional economic growth and its determinants. As a result, the specification of the panel data model still experiences variable bias that is eliminated, so that spatial econometrics is needed to recognize the existence of spatial dependence or autocorrelation (Vidyattama, 2014).

Spatial Factors in Regional Economic Growth

Regional administrative boundaries, which do not always correspond to the limits of economic activity, are among the factors that regional economists examine to determine if there is spatial autocorrelation between regions (LeSage & Pace, 2009). Economic activities that take place within or across regional boundaries, including trading or commuting, are therefore correlated with the region's overall economic success and linked to the economic performance of the involved or surrounding regions (spatial autocorrelation). The spillover effect is another term for the effects of spatial autocorrelation between nearby places (LeSage & Pace, 2009).

The Spatial Autoregressive Model (SAR), the Spatial Autoregressive Error Model (SEM), and the Spatial Autoregressive Moving Average Model (SARMA) are typically the spatial models used to ascertain whether there is spatial dependence across regions (L. Anselin, 1988). Based on each region's performance, which directly affects other regions, the SAR model evaluates the relationships between the regions. The Spatial Autoregressive (SAR) model posits the premise that the economic growth of a particular region exerts an influence on the economic growth of its neighboring regions. The SAR model takes adjacent regions' economic growth as a dependent variable for the region's own economic growth. Using the endogenous model proposed by Qu & Lee (2015), the SAR model can be expressed as follows in the equation:

$$Y_{it} = \alpha_{it} + \beta K_{it} + \gamma L_{it} + \omega H_{it} + \delta_t T_t' + \rho W Y_{it} + \eta_i + u_{it} \quad (7)$$

Where ρW is the spatial lag of the dependent variable (Y_{it}) and W is the spatial weighting matrix.

Particularly when geographic autocorrelation is not directly present in economic development variables, the SEM model arises when autocorrelation is present in the disturbance structure or error term. This equation represents the structure of the error term in spatial terms (Anselin, 1988):

$$u_{it} = \zeta W u_{it} + \varepsilon_{it} \quad (8)$$

If the spatial multiplier model is combined in equation (6), then the following equation can be used to represent the SEM model:

$$Y_{it} = \alpha_{it} + \beta K_{it} + \gamma L_{it} + \omega H_{it} + \delta_t T_t' + \eta_i + \zeta W u_{it} + \varepsilon_{it} \quad (9)$$

Where u_{it} is the error term of the panel data model and ε_{it} is the real random factor. The consequence of the SEM model is that there is no need for the assumption of homoscedasticity in the estimation. Failure to achieve homoscedasticity indicates an error in estimating the standard error of the parameter estimation. As a result, the significance of the parameter cannot be measured precisely because the estimate is not strong (Anselin, 1988; Anselin, 2003).

The third spatial model is SARMA, where spatial autocorrelation can occur in the dependent variable lag and error term. The SARMA model can be written as follows:

$$Y_{it} = \alpha_{it} + \beta K_{it} + \gamma L_{it} + \omega H_{it} + \delta_t T_t' + \rho W Y_{it} + \eta_i + \zeta W u_{it} + \varepsilon_{it} \quad (10)$$

The SARMA model incorporates a spatial weighting matrix for the dependent variable lag and error terms in the estimation of the equation model. In order to establish the significance of spatial elements in regional development models in Indonesia, this study aims to demonstrate their importance through an analysis of the lag of the dependent variable and the error term as predictors of regional economic growth in the country.

Data and Variables

The objective of this study is to analyze the impact of human capital characteristics and spatial determinants on economic growth across different regions in Indonesia, utilizing the theoretical framework of endogenous growth theory. The dataset employed in this study consists of panel data including 416 regencies and 98 municipalities in Indonesia throughout the period of 2016-2020. The variable representing economic growth is operationalized as income per capita, while the variables that are considered independent include investment, labor, human capital, trade openness, economic structure, and transportation infrastructure. The measurement of human capital is conducted through the utilization of the AHDI approach, as formulated by Windhani et al. (2022). This approach encompasses various dimensions, including education, economy, longevity, gender empowerment, democracy, and health quality. Table 1 and Table 2 provide a summary of the data and research factors utilized in the study.

Main Issues of Spatial Effects

The consideration of spatial dimensions holds significant relevance within the context of regional economic deliberations. The point at which the administrative boundary of an area transitions into the entity boundary of the same region. According to LeSage and Pace (2009), there is often a discrepancy between administrative boundaries and the boundaries that delineate economic activities across areas. This study uses spatial analysis techniques to examine the unique spatial characteristics that exist among different regencies and cities. The analysis of spatial information in a region allows for the examination of the spatial characteristics of its adjacent regions, and can also aid in identifying patterns of functional links between these regions (Stillwell & Clarke, 2006; LeSage & Pace, 2009). The geographical configuration of the area is characterized by a greater presence of water boundaries. Conversely, there is a notable abundance of administrative

Table 1. Summary of Data and Research Variables for Human Capital using AHDI approach

Variable	Symbol	Definition of Operational Variable	Unit
Human Capital with AHDI Approach:	AHDI	A measure of human capital acquired by a district/city area in Indonesia by modifying the Human Development Index (HDI), using the dimensions of education, economy, longevity, gender empowerment, democracy, and health status.	Percentage
Education Dimension:	Education	The arithmetic mean of RLS and HLS indices	
1. Mean years of schooling	MYS	Average old school completed population in the level of formal education	Year
2. Expected years of schooling	EYS	The length of school the child is expected to complete at a certain age in the future.	Year
Economic Dimension:	Economic	Index to measure economic performance	Percentage
Adjusted per capita spending	PPP	Value of spending per capita adjusted for purchasing power parity.	Rupiah
Longevity Dimension:	Longevity	Index to measure longevity	Percentage
Longevity	LE	The average number of years a person has at birth.	Year
Gender Empowerment Dimension	Gender	An index that measures the role of women in the field of life (women's involvement in parliament, as professional staff, and women's income contribution in the family).	Percentage
Democracy Dimension:	Democracy	The arithmetic mean of PID, EDUC, and KES.	Percentage
1. Percentage of completion of criminal acts	PID	The proportion of completion of criminal acts by law enforcement agencies compared to the total number of crimes that occurred.	Percentage
2. Education budget	EB	The ratio of government expenditure allocated to education in relation to the overall budget.	Percentage
3. Health budget	HB	The allocation of government funds towards healthcare in different regions relative to the overall budget.	Percentage
Health Quality Dimension:	HEALTH	Arithmetic average of RUM, AIR, SAN, LIS, FASKES and NAKES	Percentage
1. Adequate housing access		Percentage of residents who have their own house with livable	
2. Access to proper drinking water	HOUSE	quality.	Percentage
		Percentage of the population that can access drinking water needs	
3. Access to proper sanitation	WATER	from proper drinking water sources.	Percentage
		Percentage of the population that has adequate and sustainable sanitation.	
4. Access to electricity	SAN	The proportion of individuals within the population who have ability to access electric lights through the State Electricity Company.	Percentage
5. Health facilities	ELTC		
		Several health centers.	Percentage
		Several doctors.	
6. Health workers	HOSP		Unit
	DOCT		Head Account

Source: researcher's elaboration (2023).

Table 2. Summary of Data and Research Variables using Labor

Variable	Symbol	Definition of Operational Variable	Unit
Labor	LABOR	Total manpower.	Head Account
Gross Regional Domestic Product (GRDP) per capita	GROWTH	Total GRDP divided by the total population.	Million Rupiah
Economic Structure:			
Agricultural sector	AGRI	The ratio between the value added of the agriculture sector and the total Gross Regional Domestic Product (GRDP).	Percentage
Manufacture sector	MANU	The ratio between the value added of the manufacturing sector and the total Gross Regional Domestic Product (GRDP).	Percentage
Services sector	SERV	The ratio denoting the contribution of the service sector's added value to the overall Gross Regional Domestic Product (GRDP).	Percentage
Mining sector	MINING	The ratio of the value added generated by the mining sector to the overall Gross Regional Domestic Product (GRDP).	Percentage
Trade Openness	TRDS	The regional disparity in the trade balance between commodities and services.	Percentage
Highway infrastructure	ROADS	The overall length of the roadway.	Kilometer
Investment	INV	The ratio between Gross Fixed Capital Formation and Gross Regional Domestic Product (GRDP).	Percentage

Source: researcher's elaboration (2023).

divisions in the form of regencies and municipalities. According to Rey (2001), the reduction in the size of administrative areas facilitates enhanced geographical connectivity between regions due to the diminishing barriers to economic activity. Hence, it is imperative to establish empirical evidence about the impact of spatial factors on the economic development of regencies and municipalities in Indonesia.

Spatial Weighting Matrix

The design of the spatial weighting matrix is a crucial element in incorporating spatial dependency into the analysis of regional economic growth to ensure accuracy and validity. The spatial weighting matrix is a symmetric matrix of size *nxn* that quantifies the degree of proximity between different regions, hence reflecting the strength of their interrelationships. The weighting matrix utilized in this study was derived by considering the closeness and distance variables among the sites under investigation. There are several methods available for determining the weighting matrix, including linear contiguity, rook contiguity, bishop contiguity, and queen contiguity.

Linear contiguity is a region adjacent to other regions on the right and left margins. Rook contiguity is a neighboring area if it touches on each side. Bishop contiguity is a neighboring area on each corner. Queen contiguity is a neighboring area if it touches edges and corners (Anselin, 1988). This study uses the spatial weight matrix that considers the junction of the corner edges, also known as Queen Contiguity. Areas that are in contact with neighboring areas are given a value of 1, and zero if they are not in contact with neighboring areas. The spatial weighting matrix using the Queen contiguity of 416 regencies and 98 municipalities in Indonesia is as follows:

$$W = \begin{bmatrix} w_{1;1} & w_{1;2} & \cdots & w_{1;257} & \cdots & w_{1;514} \\ w_{2;1} & w_{2;2} & \cdots & w_{2;257} & \cdots & w_{2;514} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ w_{257;1} & w_{257;2} & \cdots & w_{257;257} & \cdots & w_{257;514} \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ w_{514;1} & w_{514;2} & \cdots & w_{257;257} & \cdots & w_{514;514} \end{bmatrix} = \begin{bmatrix} 0 & 1 & \cdots & 0 & \cdots & 0 \\ 1 & 0 & \cdots & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 0 & \cdots & 0 \end{bmatrix}$$

Where subscriptions are the weight of each region's boundary with other regions.

Spatial Autocorrelation Framework

The Moran's I test is utilized to detect the existence of spatial autocorrelation among the locations of observations. The formula utilized for the Moran's I test is expressed as follows (Ragdad Cani & Mendez, 2020):

$$I_t = \frac{N}{\Sigma_{i=1}^{n}\Sigma_{j=1}^{n} W_{i,j}}\left[\frac{\Sigma_{i=1}^{n}\Sigma_{j=1}^{n} W_{i,j}(X_i-\bar{X})(X_j-\bar{X})}{\Sigma_{i=1}^{n}(X_i-\bar{X})^2}\right] \quad (11)$$

Where I_t is Moran's global index; N is number of spatial observations; X_i is variable observation *i*; X_i is variable observation *j*; $\bar{X}$ is mean of the variable; $W_{i,j}$ is spatial weight between observations i and j. Moran's index values range from -1 < I < 1 with hypothesis testing $H_0 : I = 0$ (no spatial autocorrelation) and $H_0 : I \neq 0$ (there is spatial autocorrelation).

Moran's global spatial autocorrelation analysis will result in the division of the territory into four quadrants due to the scattered plot. Quadrant I refer to a collection of high-high (HH) regions, often known as hot spot locations. These areas are characterized by having high variable values, which are bordered by nearby areas that also exhibit high values. Quadrant II can be characterized as the low-high (LH) zone, wherein areas exhibiting low scores are encompassed by areas displaying high scores. Quadrant III refers to a collection of regions characterized by low-low attributes, also known as cold spot locations. These areas have low scores and are flanked by nearby regions that also display low scores. Quadrant IV can be characterized as the region exhibiting high-low area (HL) grouping, wherein areas with high variable values are next to areas with low values. The equation for the univariate version of Moran's I can be expressed as follows:

$$I = \frac{\Sigma_i \Sigma_j w_{ij} x_i x_j}{\Sigma_i x_i^2} = \frac{\Sigma_i (x_i \Sigma_j w_{ij} x_j)}{\Sigma_i x_i^2} \quad (12)$$

In this study, Moran's I differential is employed to categorize fixed location effects by discerning the variables. The utilization of local spatial autocorrelation using local Moran's statistics (Anselin, 2003), is employed to determine the importance of geographical clusters or spatial outliers in each location. The regions of utmost importance are the spatial groupings that exhibit statistical significance. The hot spot region is considered the most prominent place inside the high-high zone. The hot spot area holds considerable importance within the low-low area groups. The local equation for each region and year, as formulated by Moran, is presented as follows (Anselin, 1988):

$$I_k = \left(\frac{X_i-\bar{X}}{m_0}\right)\Sigma_{j=1}^{n} w_{kj}\left(X_j-\bar{X}\right) \quad (13)$$

$$m_0 = \Sigma_{k=1}^{n}\frac{(X_k-\bar{X})^2}{p} \quad (14)$$

On average, the global Moran I value is obtained by analyzing the findings of the Local Indicator of Spatial Association (LISA) value for each region (Luc Anselin, 2003). The utilization of LISA analysis enables the identification of noteworthy spatial relationship grouping patterns pertaining to area values, encompassing both low and high values. Spatial associations in LISA analysis can be classified into four quadrant groups, which are igh-High (HH) or hot spot areas, Low-High (LH), High-Low (HL), and Low-Low (LL) or cold spots. The high-high (HH quadrant) refers to a spatial configuration wherein regions exhibit equivalent and substantial Local Indicators of Spatial Association (LISA) values. The low-high quadrant (LH quadrant) exhibits a spatial correlation with a comparatively lower and statistically significant Local Indicators of Spatial Autocorrelation (LISA) value in comparison to the surrounding region. The HL quadrant refers to a specific geographical region that exhibits a spatial correlation with a stronger and more pronounced Local Indicators of Spatial Association (LISA) score in comparison to the adjacent areas. The low-low (LL) quadrant, also known as chilly patches, refers to specific regions that exhibit a spatial correlation with LISA values that are consistently lower than those of the surrounding areas, and these deviations are statistically significant. The utilization of LISA analysis can also serve the purpose of identifying major areas of growth, commonly referred to as "hot spots" or the "HH quadrant," as well as places that are experiencing slower development, known as "cold spots" or the "LL quadrant," within a given region.

3. Result and Discussion

Distribution of Indonesia's Regional Economic Growth

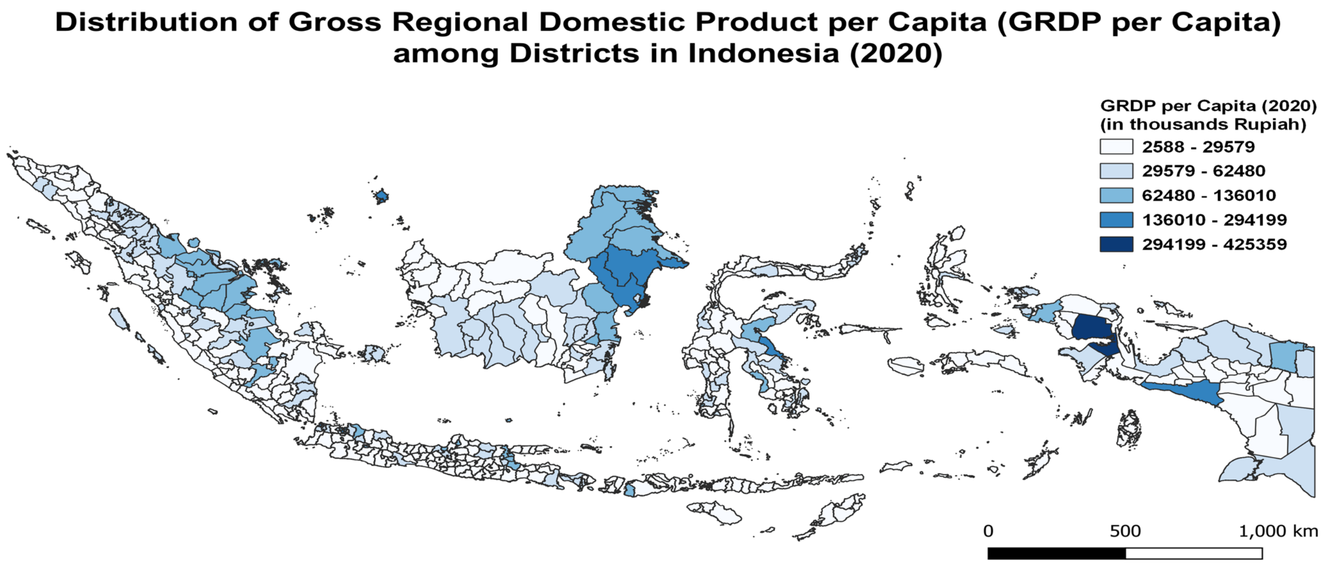
The economic growth variable is frequently employed as a metric to assess area economic advancement, serving as an indicator of economic development. The Gross Regional Domestic Product (GRDP) per capita is commonly employed as a proxy for examining the economic growth of a region. Figure 1 shows the distribution of GRDP per capita of among regencies and municipalities in Indonesia in 2020. The distribution pattern of Gross Regional Domestic Product (GRDP) per capita among regencies and municipalities in Indonesia continues to exhibit a state of inequality. The per capita Gross Regional Domestic Product (GRDP) in regions outside of Java in Indonesia exhibits a higher dominance compared to locations within Java, which tend to demonstrate lower levels.

However, even though the mapping results show that most regions in Java tend to have low per capita GRDP in Indonesia, except the area special region capital city of Jakarta (DKI Jakarta), City of Kediri and City of Surabaya have high per capita GRDP in Indonesia. As we know, DKI Jakarta and Surabaya City are one of the centers of economic activity in Indonesia whose economic structure is mostly contributed by the manufacturing and service sectors. Regions outside Java Island that have high per capita GRDP are dominated by regions that have ownership of mining materials, such as the Anambas Islands, Bontang City, Mimika Regencies, and Teluk Bintuni Regencies. The Anambas Islands Regencies, Bontang City, Mimika regencies and Teluk Bintuni regencies are small areas and have a relatively smaller population than other regions in Indonesia, but these regions have an economic structure that is very dominant in the mining sector. The dominance of the mining sector in these regions even reaches more than 80% of GRDP, such as the Anambas Islands region which reached 82%.

The findings of the analysis on the distribution of per capita income among regions in Indonesia indicate that while the majority districts in the country exhibit an economic structure that is predominantly reliant on the agricultural sector, the mining and manufacturing sectors serve as the primary drivers of the Indonesian economy. The mining and manufacturing sectors are known for their significant contributions to the economy in terms of added value, hence resulting in a greater per capita Gross Regional Domestic Product (GRDP) for the region (Mejía, 2020). Regions that are centers of economic growth in Indonesia tend to have a manufacturing economy structure. This shows that the manufacturing sector is still important in the structure of the economy in Indonesia, shown by a contribution of 16.10 % (BPS Statistics Indonesia, 2021). The manufacturing sector is the dominant sector in the centers of economic growth in Indonesia, such as DKI Jakarta and the City of Surabaya. Regions in close proximity to economic hubs frequently have comparable economic attributes, as seen by the presence of agglomeration regions like Jabodetabek (Jakarta-Bogor-Depok-Tangerang-Bekasi) in West Java and Gerbangkertosusilo (Gresik-Bangkalan-Mojokerto-Surabaya-Sidoarjo-Lamongan) in East Java.

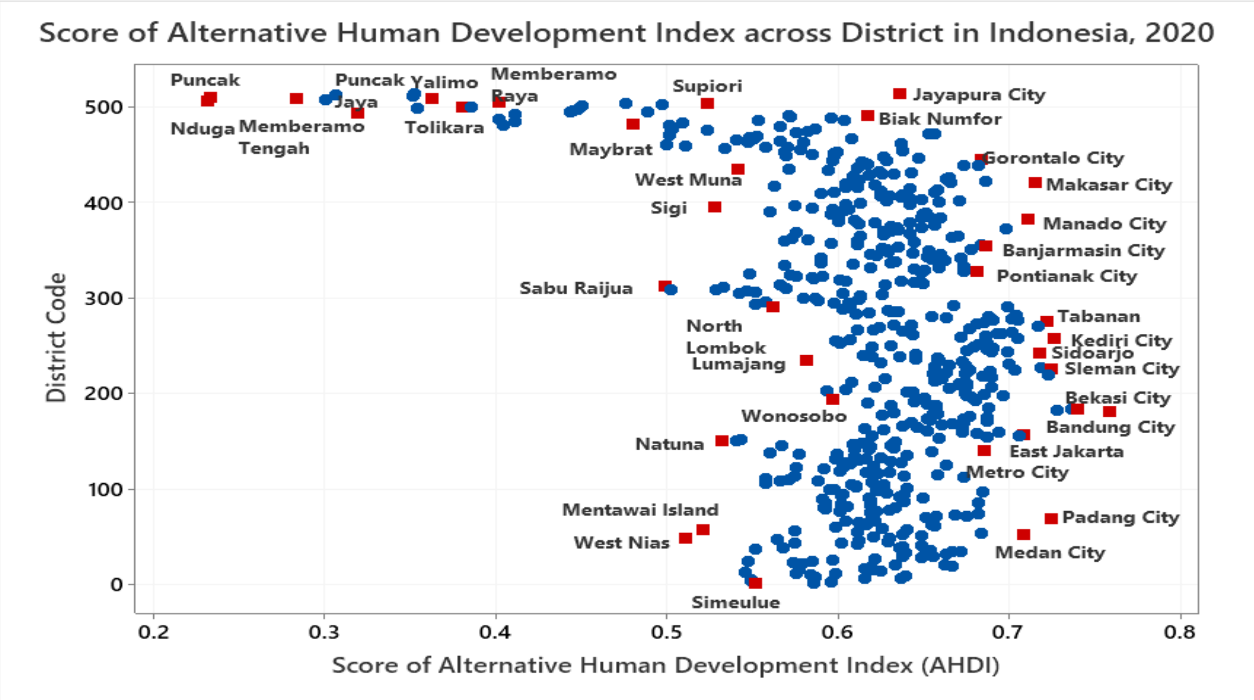
Distribution of Human Capital in City Districts in Indonesia with the AHDI Approach

Regions characterized by a substantial degree of economic growth will subsequently exhibit a commensurate amount of human capital of superior quality. The assessment of human capital in Indonesia by the AHDI framework, reveals a disparity in the state of human capital between the western and eastern regions of the Indonesia. The regions located in western Indonesia have comparatively greater levels of human capital in comparison to the regions situated in eastern Indonesia. Figure 2 illustrates the allocation of human capital among different areas in Indonesia using the AHDI methodology.



Source: data processed by researchers (2023)

Figure 1. Distribution of Regional GRDP per Capita in Indonesia in 2020 (in thousands of Rupiah)



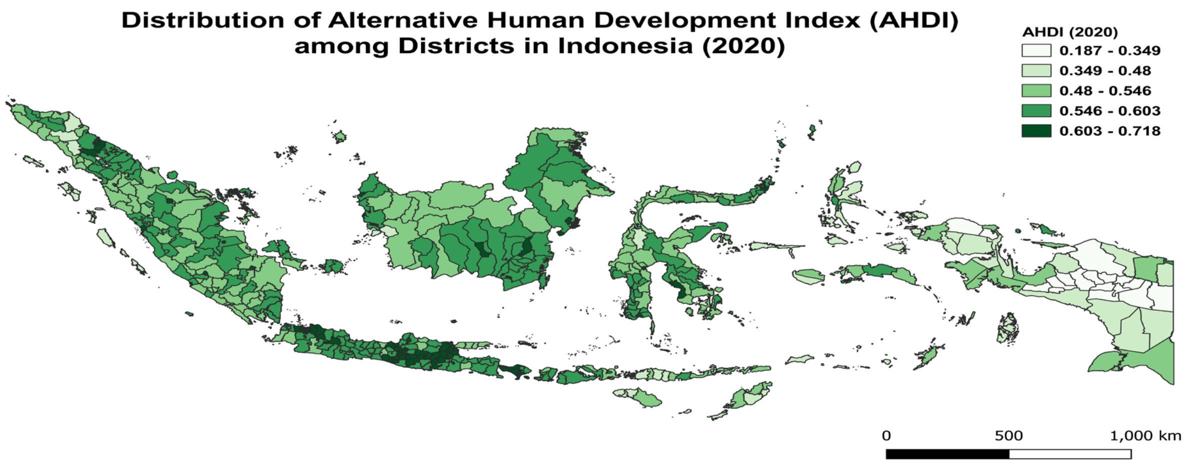
Source: processed data (2023)

Figure 2. The Level of Human Capital in Indonesia Based on the AHDI Approach

Figure 2 illustrates the distribution of human capital levels in Indonesia using the AHDI methodology. The majority locations in western Indonesia exhibit high AHDI scores. The AHDI scores in Eastern Indonesia are generally observed to be low. Bandung City in Indonesia exhibits the greatest AHDI score, reaching a value of 0.7579, while the regencies of Nduga regency demonstrate the lowest AHDI score, with a value of 0.2320. The regencies and municipalities of Papua Island are characterized by the lowest level of human capital in Indonesia. Most regencies and municipalities in regions Papua have low AHDI scores, such as Nduga, Puncak, Memberamo Tengah, Memberamo Raya, Tambraw, and others. Low AHDI scores in Indonesia are mostly dominated by areas in Papua. The low value of AHDI is influenced by the low value of the human capital dimension in almost all aspects, such as education, economy, health, democracy, and gender empowerment. The level of human capital between regions in Indonesia is uneven, where regions with a manufacturing economic structure tend to have a high level of human capital. This is in accordance with the research of Ragdad Cani & Mendez (2020) which states that human resources in Indonesia are more concentrated in areas that are the center of economic growth, where the economic structure is more dominant in the manufacturing and service sectors. Based on research by Mulyaningsih et al. (2019) regions with a manufacturing economic structure will be interested in generating higher wages (wage premium) than other economic sectors. The manufacturing sector has a premium wage because this sector requires high labor skills. Other research conducted by Suparman & Muzakir (2023) and Sofilda et al. (2023) also states that a high level of human capital will encourage regional economic growth, so that regions with high levels of GRDP per capita also have high human capital.

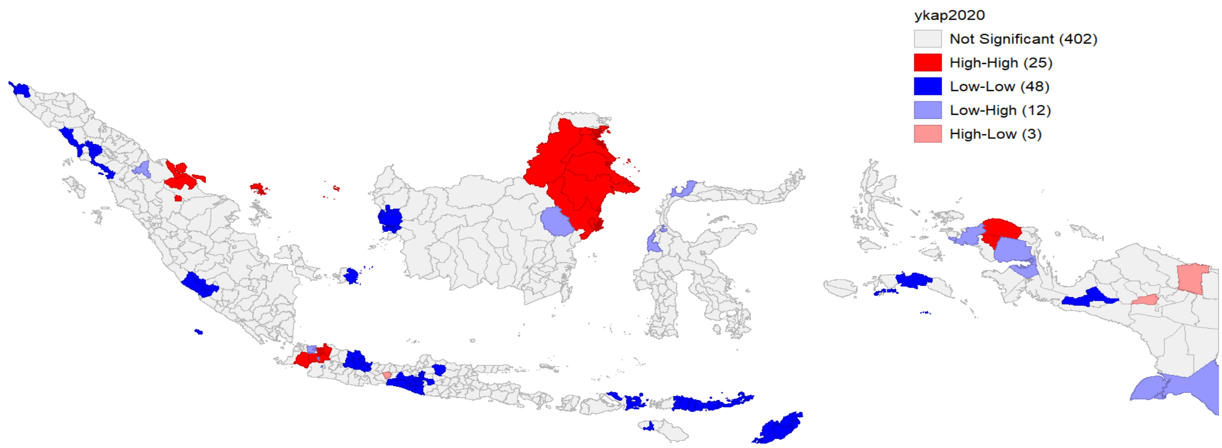
The distribution of human capital in Indonesia, as observed through the AHDI technique, reveals an inequitable state across different regions. Particularly when seen within the context of Western and Eastern Indonesia. The level of human capital in the western region of Indonesia is generally higher compared to the eastern region of Indonesia. Figure 3 illustrates the spatial thematic maps depicting the distribution of human capital among regencies and municipalities in Indonesia.

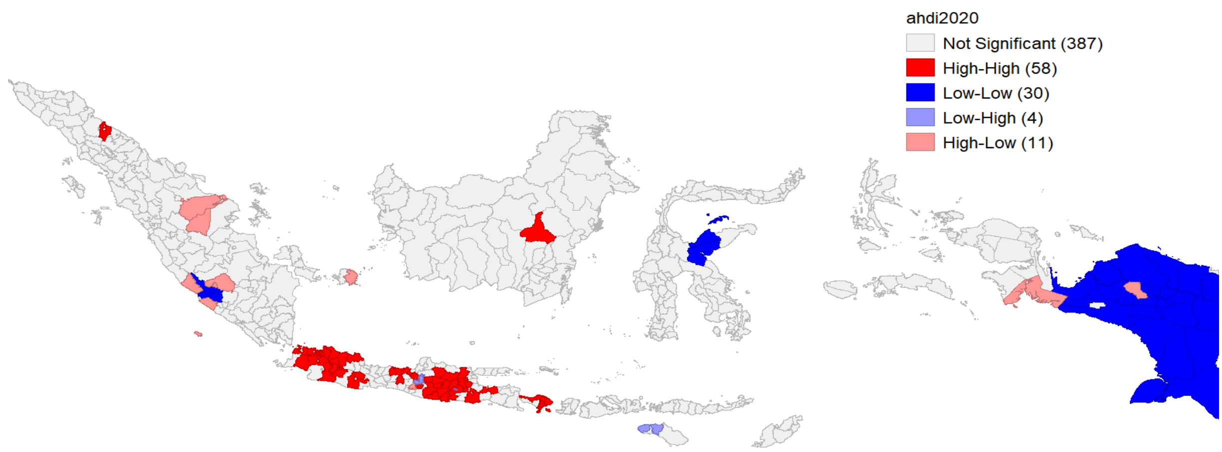
The distribution pattern of human capital among regencies and municipalities in Indonesia reveals a notable concentration of high levels of human capital in regions located in Java. Papua Island is identified as the geographical area within Indonesia that has the most limited degree of human capital. The phenomenon seen in Indonesia regarding the quality of human capital exhibits an intriguing pattern, wherein locations characterized by high per capita income tend to display lower levels of human capital quality. This trend is particularly evident in numerous regions across Papua. Despite the relatively high per capita income, there remains a notable deficiency in the quality of human capital. In contrast, Java Island exhibits a very low per capita income, although it is characterized by a comparatively elevated degree of human capital quality in relation to other geographical areas. The issue of human capital disparity remains a significant obstacle to growth in Indonesia. The regions in Java have a relatively high level of human capital due to their substantial population size and geographical proximity to the central government and economic growth pole. Although Papua is the largest region in Indonesia, its population is very modest. One of the contributing causes to the limited development of human capital is the geographical location that is distant from the central seat of government. Furthermore, the presence of conflict areas in various regions of Papua contributes to the disparity in development, hence impeding progress. The presence of conflict zones is a contributing factor to regional disparities in development, those characterized by the presence of conflict areas sometimes exhibit a higher degree of underdevelopment compared to those without such conflicts (Peck et al., 2022).



Source: processed data (2023)

Figure 3. Thematic Map of The Distribution of Human Capital among Districts in Indonesia





Source: data processed by researchers (2023)

Figure 4. LISA Thematic Map of Economic Growth and Human Capital in Indonesia

Spatial analysis enables the examination of growth centers and impoverished regions through the utilization of Local Indicator Spatial Analysis (LISA). In regions experiencing economic growth, designated areas will be visually indicated in red as hot spots, while trailing areas will be demarcated in blue. Figure 4 displays the outcomes of the LISA analysis, which generated a thematic map illustrating the distribution of human capital among districts and cities in Indonesia. The analysis conducted by the LISA (Local Indicators of Spatial Association) method on the economic growth in Indonesia encompasses four distinct quadrants, which are referred to as high-high (HH), low-low (LL), low-high (LH), and high-low (HL) quadrants. The HH quadrant comprises 28.41% of the overall membership, followed by the LL quadrant with 54.55%, the LH quadrant with 13.64%, and finally the HL quadrant with 3.41%. The high-growth regions or economic hotspots in Indonesia share commonalities, specifically the presence of mining and manufacturing industries. The regions located in the provinces of Riau, East Kalimantan, South Sulawesi, and Papua exhibit commonalities in terms of the occurrence of mining resources, including petroleum, natural gas, coal, copper, nickel, tin, iron, bauxite, diamonds, and gold. The regions in DKI Jakarta and East Java exhibit a notable resemblance in terms of the prevalence of the manufacturing sector. Based on the LISA analysis, it can be inferred that a higher concentration of regions is observed in LL areas or cold spot areas, suggesting a tendency for economic growth in Indonesia to align with the low economic growth group. The findings derived from the LISA study of economic growth indicate that the level of economic growth observed across different regions in Indonesia can be characterized as relatively low. The majority regions in Indonesia are situated in the poor-Low quadrant (LL), sometimes referred to as cold spots. This classification indicates that a significant number of regencies and municipalities experience limited economic growth and are geographically surrounded by nearby regions that also exhibit poor levels of economic development. In essence, the phenomenon observed in Indonesia is characterized by the concentration of economic growth in regions exhibiting relatively low levels of economic performance. The economic growth across different regions in Indonesia exhibits a tendency towards being relatively modest. This can be attributed to the prevalence of an agricultural sector that dominates the economic structure in numerous locations. However, this agricultural sector typically generates limited added value to the overall economy (Vidyattama, 2014; Gunawan et al., 2019).

According to the LISA study of human capital, the HH quadrant comprises 56.31% of the total members, while the LH quadrant accounts for 3.88%. Similarly, the HL quadrant represents 10.68% of the members, and the LL quadrant constitutes 32.04% of the total. The regions characterized as human capital hot spots are primarily concentrated in the regencies and municipalities located on Java Island, while the cold spot locations are predominantly found on Papua Island. The region located on the island of Java serves as a focal point for the concentration of substantial human capital, while Papua represents an area characterized by a comparatively lower level of human capital. Based on the research conducted using the Location Indicators for Spatial research (LISA) technique, it is evident that a significant proportion of the human capital in Indonesian regencies and cities is concentrated in hot spot areas (HH Quadrant) as opposed to cold spot areas (LL Quadrant). This observation leads to the conclusion that human capital in Indonesia exhibits a tendency to aggregate in clusters characterized by elevated levels of human capital. There is a tendency for human capital to be concentrated in regions of Indonesia that exhibit high levels of human capital performance. According to the findings of the LISA research, it has been established that the distribution of human capital tends to be concentrated in specific regions on the island of Java. The predominant economic sectors in most parts of Java are manufacturing and services. The findings align with the research conducted by Mulyaningsih et al. (2019) which suggests that areas characterized by a predominant economic framework centered around manufacturing and mining industries tend to exhibit elevated levels of human capital. Regions characterized by a manufacturing and mining economic structure often exhibit a propensity for providing higher pay, sometimes referred to as premium wages. This phenomenon can be attributed to the fact that these industries necessitate a comparatively elevated degree of workforce competence in comparison to other sectors. Underdeveloped regions exhibit a higher rate of convergence in comparison to developed regions, hence enabling them to achieve a more rapid catch-up with their developed counterparts. This finding aligns with the research conducted by Ragdad Cani & Mendez (2020), which suggests that human capital in different regions of Indonesia tends to cluster together, with regions possessing high levels of human capital being grouped together. This phenomenon can be attributed to the higher rate of convergence in human capital levels observed in underdeveloped regions compared to developed regions.

Nevertheless, there remain numerous regions that are characterized as cold spot locations, primarily concentrated on the island of Papua. Java Island continues to serve as the focal point for the concentration of significant quantities of human capital inside the nation of Indonesia. Regions located outside of Java in Indonesia are characterized by relatively lower levels of human capital. The prioritization of government policy, particularly in the regions of Papua Island, stems from the prevalent low level of human capital throughout practically all areas. The expansive geographical expanse of Papua, coupled with its considerable distance from the administrative hub, has resulted in a dearth of human capital within various districts of the province. The sub-optimal level of human capital in the majority of regions in Papua can be attributed, in part, to the comparatively low average years of schooling achieved. The majority of regions in Papua exhibit an average duration of schooling that falls below the national average of 8.67 years. In order to enhance human capital in various regions of Papua, several policies can be implemented. These policies include augmenting school participation rates and enhancing educational infrastructure. This can be achieved through the establishment of a greater number of easily accessible schools, an increase in the number of teaching personnel, and the provision of specialized educational scholarships for higher education.

The findings derived from the analysis conducted by LISA have the potential to inform the development of human capital policies that are characterized by enhanced efficiency and alignment with intended objectives. The allocation of human capital policies is given precedence in cold spot areas, such as the regions of Papua, in order to mitigate disparities in comparison to other regions and address issues of inequality. The government has implemented a crucial strategy aimed at enhancing the quality of human capital in Papua by facilitating greater access to education and health infrastructure. Enhancing the quality of road infrastructure through augmented budget allocations holds significant importance in fostering connectivity across regencies and municipalities in Papua, as well as facilitating improved access to education and healthcare services. The findings shown here align with the research conducted by Affandi et al. (2019) which posited that the advancement of infrastructure within a certain region fosters the growth of human capital. Enhancing the quality of road infrastructure facilitates improved accessibility to educational and healthcare facilities. However, it is crucial to prioritize policies that enhance women's empowerment and promote democratic values to foster human capital development and stimulate regional economic growth. Enhancing women's empowerment in marginalized regions can be achieved through augmenting women's opportunities

Table 3. Moran's I Index Value

Moran's I Index Value
0.2927***
significant at level α ***1 %; **5 %; *10 %

Source: processed data (2023)

Table 4. Lagrange Multiplier (LM) Test Results

Spatial Model	Coefficient	
	The spatial weight of the lagged dependent variable (ρ)	The spatial weight of the lag variable error (λ)
Lagrange Multiplier (lag)	0,246***	
Lagrange Multiplier (error)		0,701***
Lagrange Multiplier (SARMA)	0,025	0,683 ***
significant level α ***1 %; **5 %; *10 %		

Source: processed data (2023)

to engage in economic, educational, and political domains. Enhancing women's participation in the economic sector can be facilitated by the mitigation of sex-based discrimination in the recruiting process, so affording women expanded prospects across many occupational domains. In the realm of politics, there exists a requirement for a 30 percent quota of female representation in parliamentary bodies. However, the current average in Indonesia stands at 21 percent, indicating a discrepancy between the legal quota and the actual presence of women in parliament. The government has the ability to incentivize political parties to comply with the requirements regarding women's quotas in national elections. In relation to the domains of democracy and security, it is possible for the government to enhance the efficacy of security forces in the prosecution of criminal activities, thereby ensuring societal safety and legal assurance. In addition to this, it is imperative for the government to mitigate separatist actions in various regions in order to ensure public safety and prevent any hindrance to the ongoing development efforts. According to scholarly research conducted by Ray, (2010), and Peck et al. (2022), the presence of separatist activities has the potential to impede the progress of regional development.

Estimation of the Spatial Model of Economic Growth in Cities and Regencies in Indonesia

Spatial Dependency Test Results

The outcomes of the spatial dependency examination employing Moran's I index are presented in Table 3. The value of Moran's I index, which is 0.2927, is statistically significant at the α = 1% significance level.

Moran's I index value exhibits a positive trend, suggesting the presence of a positive autocorrelation, or geographical dependency, in the economic growth patterns observed among the regencies and municipalities in Indonesia. This implies that the economic performance of a particular region will have an impact on the economic performance of its nearby regions. The economic growth model in Indonesia at the regional level incorporates substantial spatial factors.

Lagrange Multiplier (LM) Test Results

The subsequent step involves the utilization of the Lagrange Multiplier (LM) test order to detect spatial autocorrelation that arises among adjacent regions. Spatial autocorrelation may manifest in the lag of the dependent variable (ρ), the error term (λ), or both. The outcomes of the Lagrange Multiplier (LM) test are presented in Table 4.

According to the findings presented in Table 4, the LM test results reveal the presence of spatial autocorrelation in both the lagged dependent variable (ρ) and the error term (λ) across regions in Indonesia. Therefore, empirical evidence supports the assertion that the Spatial Autoregressive Moving Average (SARMA) model is the most effective spatial model. The spatial dimensions exhibit a favorable impact, as evidenced by the values of ρ and λ, which are 0.025 and 0.683, respectively. The spatial dimension exerts a beneficial impact on adjacent regions. This research used a spatial regression model to examine the impact of spatial variables on the economic growth of regencies and municipalities in Indonesia. The estimation model of economic growth uses panel data to reduce the estimation model's weaknesses and variable bias (Chen & Gupta, 2006; Teixeira & Queirós, 2016; Sharma, 2018). The economic growth regression model is used to find determinants that influence regional economic growth. The variable used in this study is per capita Gross Regional Domestic Product (GRDP per capita) as the dependent variable, whereas the independent variables used are an investment, labor, human capital, economic structure, trade openness, and road infrastructure. The estimation of the spatial model that will be used using panel data is as follows:

Non-spatial models:

$$Growth_{it} = \alpha_{it} + \beta_1 INV_{it} + \gamma_1 LABOR_{it} + \omega_1 AHDI_{it} + \beta_2 AGRI_{it} + \beta_3 MANU_{it} + \beta_4 SERV_{it} + \beta_5 MINING_{it} + \beta_6 TRDS_{it} + \beta_7 ROADS_{it} + \varepsilon_{it} \quad (15)$$

Spatial Autoregressive Moving Average (SARMA) Model:

$$Growth_{it} = \rho WY_{it} + \alpha_{it} + \beta_1 INV_{it} + \gamma_1 LABOR_{it} + \omega_1 AHDI_{it} + \beta_2 AGRI_{it} + \beta_3 MANU_{it} + \beta_4 SERV_{it} + \beta_5 MINING_{it} + \beta_6 TRDS_{it} + \beta_7 ROADS_{it} + \delta_t T_t' + \eta_i + \zeta W u_{it} + \varepsilon_{it} \quad (16)$$

Table 5 presents a comparative analysis of the estimation outcomes obtained from both the non-spatial and spatial regression models applied to examine the regional economic growth in Indonesia. The panel data model (non-spatial) reveals that several variables, namely human capital, investment, the manufacturing sector, mining, trade openness, and long-road infrastructure, exhibit a statistically significant positive impact on regional economic growth in Indonesia. Table 5 demonstrates that the presence of a fluctuating workforce, the agricultural industry, and the impact of the service sector exert a noteworthy adverse influence on the economic growth of different regions within Indonesia. Thus, it may be said that human capital plays a pivotal role as the primary determinant of economic growth in Indonesia.

The utilization of a geographical model yields disparate outcomes in contrast to the utilization of panel data. The variables of human capital, investment, manufacturing sector, mining, trade openness, and road infrastructure exhibit a statistically significant and beneficial impact on the economic growth observed across regencies and municipalities in Indonesia. The impact of the agricultural and service sectors on regional economic growth in Indonesia is characterized by a fluctuating contribution that has a notable negative influence. There is no discernible impact of the labor variable on interregional economic growth in Indonesia. The utilization of the geographical model reveals that human capital remains the primary factor influencing economic growth across different regions in Indonesia. This suggests that the idea of endogenous growth might be applied to examine the phenomenon of economic expansion across different regions in Indonesia. The variation in human capital levels is a determining factor in the economic advancement of different regions within Indonesia. locations characterized by a high caliber of human capital tend to exhibit a greater degree of economic advancement in comparison to other locations. The degree of regional economic advancement is influenced not solely by economic variables, but also contingent upon non-economic factors. Multiple prior research has posited that the economic development of a certain locality is not solely determined by economic variables, but is also influenced by social aspects (Pelinescu, 2015; Dicker et al., 2018; Ali et al., 2018). The findings of this regional analysis align with the conclusions drawn by Vidyattama (2014), Ragdad Cani & Mendez (2020) and Rahman et al. (2022), which claim that human capital exerts a favorable impact on economic growth.

Nonetheless, investment is a variable that spatially has a positive and significant effect on regional economic growth. It does not only affect the increase in the output production capacity of a region (Jhingan, 2012) but also encourages an increase in capital stock. Regions with high levels of investment tend to have higher growth rates compared to other regions. More investment occurs in areas with a manufacturing and mining economic structure that generates higher added value compared to other sectors. This result is in line with the study of Vidyattama (2014), Dewanta et al. (2017), Yulianita et al. (2017), and Ahumada & Villarreal (2019), which state that investment has a positive effect on regional economic growth. Meanwhile, regions dominated by the manufacturing and mining sectors tend to have high economic growth in Indonesia (Vidyattama, 2014; Diebolt & Hippe, 2019). The contribution of the manufacturing sector in Indonesia in 2020 is dominated by regions on the island of Java. Municipal regencies on Java Island are hot spot areas or centers of growth for the manufacturing sector in Indonesia, so they have higher economic growth than areas outside Java. Regions with ownership of unique natural resources (mining materials) tend to have human capital with high levels of education and skills. Workers with higher levels of education and skills tend to earn higher wages. A high wage rate will attract a large number of skilled workers to gather in the area (Mulyaningsih et al., 2019), which results in a higher economic growth rate than in other regions accordingly.

Road infrastructure in Indonesia has been found to have a significant and positive influence on the economic growth of the respective regions. The longer the highway infrastructure in an area, the easier connectivity between regions will be. Easy connectivity will increase economic activity between

Table 5. Comparison of Panel Data Model and SARMA Model Results

Variable	Non-Spatial Model (Random Effect Model)		Spatial Autoregressive Moving Average (SARMA) Model	
	Coefficient	Standard error	Coefficient	Standard error
Constanta	2.245***	0.4402***	2.645***	0.128
$AHDI_{it}$	1.235***	0.1247***	0.736***	0.056
$LABOR_{it}$	-0.130**	0.0355**	0.013	0.009
INV_{it}	0.128**	0.0465**	0.010**	0.004
$AGRI_{it}$	-0.008**	0.0020**	-0.007***	0.001
$MANU_{it}$	0.009***	0.0025***	0.008***	0.001
$SERV_{it}$	-0.003	0.0070	-0.015***	0.003
$MINING_{it}$	0.013***	0.0024***	0.0014***	0.0003
$TRDS_{it}$	0.002**	0.0009**	1.27×10^{-09}***	1.78×10^{-10}
$ROADS_{it}$	0.014**	0.0089	0.010**	0.004
Prob F		0.000		0.000
R-squared (R^2)				0.3158
R^2- within		0.2168		
R^2- between		0.6274		
R^2- overall		0.6211		
W-ρ			0.025	0.215
W-λ			0.683***	0.000

*** significant on α=1%; ** significant on α=5%; * significant on α=10%

Source: processed data (2023)

regions, which causes the region's economic level to be more advanced. Regions on the island of Java have relatively more roads compared to those outside Java, making the distribution of goods and services between regions easier. This finding is consistent with the research conducted by Vidyattama (2014), Ismail & Mahyideen (2016), Munir et.al. (2018), and Banerjee et al. (2020) suggests that the presence of infrastructure has a favorable impact on the economic development of a regions. Highway infrastructure is related to increasing regional connectivity with other regions. Increased connectivity between regions will help improve their interaction with the surrounding areas, thereby encouraging faster economic growth. Trade openness refers to the degree of economic engagement and exchange between different regions. There is a positive correlation between the level of interaction in economic activity among different regions and the resulting regional economic growth. The limited impact of trade openness on regional economic growth in Indonesia can be attributed to the fact that only a select few regions are recognized as significant drivers of economic development. Moreover, the primary areas of economic expansion are predominantly controlled by regions located on the island of Java. locations outside of Java continue to experience economic disparities in comparison to Java. This discrepancy is evident as the majority of economic activity in various locations across Indonesia strongly relies on the production of goods and services originating from Java. This finding is consistent with the research conducted by Vidyattama (2014), Munir et al. (2018), Messakh et al. (2022), and Nawir et al. (2023) suggests that the presence of road infrastructure yields positive effects on the economic growth of a certain region. The extent of road infrastructure given area directly influences the level of connectivity and accessibility between locations. The establishment of efficient inter-regional connectivity will serve to enhance the seamless transfer of products and services, hence encouraging a notable expansion in economic activity. The acceleration of economic activity is expected to support regional economic growth.

Contribution of the agricultural and services economic sector variables have a negative effect on economic growth in Indonesia. The structure of the agrarian and service economy has slowed down the economic growth of urban districts in Indonesia. This condition is caused by the productivity of the agricultural sector, which is still low and does not have good quality compared to other countries. A quality agricultural product processing system increases the durability of agricultural products so that they can compete with other countries and increase the added value of the agricultural sector. In addition, the amount of agricultural land has decreased due to the conversion of land to housing or the manufacturing sector, causing a smaller contribution of the agricultural sector to GRDP. Another factor is Indonesia's agricultural products which are still unable to compete with other countries in terms of price and product packaging, so the products spoil quickly and are vulnerable to price changes. This result is in accordance with a study Agussabti et al. (2022) suggest that agricultural sector production in Indonesia is still not competitive compared to other countries due to the use of agricultural technology that is not yet modern. The use of modern agricultural technology will improve the production process so that the productivity and quality of the agricultural sector will increase. Processing good quality agricultural products will increase the competitiveness of products in international markets. Meanwhile, the service sector in Indonesia has not become the dominant sector for the economy of most regencies and municipalities in Indonesia. On the other hand, the service sector in Indonesia is only dominant in urban districts on the island of Java, which are geographically close to the centers of economic growth, such as Jakarta and Surabaya. Apart from that, during the COVID-19 pandemic, the service sector was one of the sectors affected because most community activities in various fields were restricted to reduce the impact of COVID -19. Restrictions on community activities have an impact on reducing production in the service sector, for example, transportation services. The decline in the number of consumers in the service sector has resulted in a significant reduction in output in the service sector. Studies Brody et al., (2023) state that the COVID-19 pandemic has reduced income in the service sector. On the other hand, the Covid-19 pandemic has created high volatility in the production sector, especially industry and services due to uncertain conditions in the economy. Conditions of uncertainty in the economy mean that the production sector tends to grow stagnantly due to declining production (Brody et al., 2023).

Labor spatially has no significant effect on GRDP per capita with a coefficient value of 0.013. The labor force between districts and cities in Indonesia remains unequal. Based on (BPS Statistics Indonesia, 2021) data, 57.16 % of the workforce in Indonesia have low education, i.e., lower than junior high school, while those with higher education (diploma or degree) only account for 12.33 %. There exists a positive correlation between the relatively low educational attainment of the workforce and the related low levels of skills and productivity output. The presence of a larger workforce with little educational attainment is likely to have a negative impact on output productivity, hence leading to a decline in the region's economic growth. The findings of this study are inconsistent with the research conducted by Barro (2001), Barro et al. (2013), Bangun (2020), Hjazeen et al. (2021) and Malau & Sembiring (2022) states that the number of highly educated workers is associated with a high level of output productivity in an area.

The use of a spatial model in the estimation of economic growth in Indonesia indicates a significant finding: spatial elements reflect a positive impact, as seen by the spatial lag weight value of the dependent variable (ρ) of 0.025 and the error term (λ) of 0.683. This implies that the economic expansion of a particular location has an impact on the economic growth of other regions, attributable to both the extended impact of the dependent variable and the residual term. According to the LM test, the spatial model that indicates the highest level of goodness-of-fit is SARMA. The formulation of the SARMA equation model is as follows.:

$$\text{growth}_{it} = 0{,}025 \sum_{j=1, i\neq j}^{n} w_{ij} u_j + 2{,}645^{***} + 0{,}736\ \text{AHDI}_{it}^{***} + 0{,}013\ \text{lnLABOR}_{it} + 0{,}010\ \text{lnINV}_{it}^{**} - 0{,}007\ \text{AGRI}_{it}^{***} + 0{,}008\ \text{MANU}_{it}^{***} - 0{,}015\ \text{SERV}_{it}^{***} + 0{,}0014\ \text{MINING}_{it}^{***} + 1{,}27\text{x}10^{-09}\ \text{TRADE}_{it}^{***} + 0{,}010\ \text{lnROADS}_{it}^{**} + 0{,}683^{***} \sum_{j=1, i\neq j}^{n} w_{ij} u_j + \varepsilon_{it} \quad (17)$$

significant α : *** 1%; ** 5% and *10%

The identification of spatial linkages between regencies and municipalities in Indonesia is accomplished through the utilization of spatial weighting matrices. The significance of the spatial weighting matrix between regencies and municipalities in Indonesia can be observed by the values of the lag error term variable (λ) at 0.0251 and the dependent variable lag variable (ρ) at 0.6827. Spatial links exhibit a positive impact, indicating the existence of spatial interdependence in the economic growth of different regions within Indonesia. This interdependence is observed in both the lag of the dependent variable and the error term. This findings in line with the research conducted by Aspiansyah & Damayanti (2019), and Xu & Li (2020) suggest that smaller areas have greater spatial interactions with neighboring regions. In Indonesia, regencies and municipalities are inherently inclined to form associations with adjacent territories that share specific features or common qualities. Spatial study reveals that spatial factors also play a significant role in determining the economic growth disparities among different regions. The economic conditions present in a particular location have a significant impact on the economic growth experienced by nearby regions. Economic activities may transcend the official limits of a certain region. The economic interactions between proximate regions demonstrate a primarily functional association. For instance, the economic activities occurring within the city of Surabaya have a consequential impact on the neighboring regions, namely Gresik, Sidoarjo, and Jombang. Consequently, these locations can be considered as satellite regions in relation to the economic activity of Surabaya. The findings presented here are consistent with previous studies conducted by Vidyattama (2014), Anwar (2017), Suparman & Muzakir (2023), which have established that geographical factors exert a significant influence on the economic growth of regions.

The economic growth in the central areas of economic growth will be followed by other regions that are located around the centers of economic growth. Regions near the center of economic growth are inclined to present a more pronounced rate of economic expansion, in comparison to regions positioned farther away from the center of economic growth. Regencies and municipalities in West Java that share direct borders with Jakarta, the main center of business activity in Indonesia, present a comparatively greater rate of economic growth when compared to regions located farther away from this economic center. The establishment of a policy focused on encouraging the development of new economic growth centers holds significant importance, particularly in regions situated beyond Java that are geographically distant from Jakarta. This policy seeks to stimulate economic progress in parts of Indonesia that continue to experience comparative underdevelopment.

4. Conclusion

Many recent studies have been conducted to explain the regional economic growth of urban districts in Indonesia. The geographical uniqueness of regions in Indonesia where the boundaries are mostly in the form of waters, thereby inhibiting the possibility of spatial aspects occurring. However, on the other hand, having a small administrative area such as a large regencies and municipalities, where there are very few obstacles to economic activity raises the possibility of high spatial dependence between regions. So that the spatial aspect is important to consider in the regional economic growth regression model, to prove its effect on economic growth in Indonesia.

This study aims to investigate the influence of human capital and spatial aspects on the regional economic growth of urban districts in Indonesia. By using the theoretical framework of endogenous growth, the use of spatial model specifications for regional economic growth in Indonesia shows that human capital has a positive and significant effect on the economic growth of urban districts in Indonesia. Location or spatial aspects have a positive effect on the economic growth of urban districts in Indonesia. The spatial aspect has a positive effect on the economic growth of urban districts in Indonesia. This means that the economic performance of a region affects its neighboring regions. The study of LeSage and Pace (2009) states that smaller administrative boundaries cause small economic obstacles, and the economic performance of neighboring regions will be interrelated. Making a policy to increase regional economic growth should therefore consider the determinants of human capital and spatial aspects between districts and cities in Indonesia. Based on the spatial model analysis of regional economic growth, the variables of human capital and spatial aspects are the main determinants of the economic growth of urban districts in Indonesia. Increasing regional economic growth requires a policy that prioritizes the improvement of human capital quality. Given the importance of the spatial aspect in regional economic growth, policies must be carried out in synergy between adjacent regions, so that they are better targeted and efficient.

References

Adam, L., & Dharma Negara, S. (2015). Improving Human Capital through Better Education to Support Indonesia's Economic Development. *Economics and Finance in Indonesia*, *61*(2).

Affandi, Y., Anugrah, F. D., & Bary, P. (2019). Human Capital and Economic Growth Across Regions: a Case Study in Indonesia. *Eurasian Economic Review*, *9*(3), 331–347. https://doi.org/10.1007/s40822-018-0114-4

Agusalim, L., Anggraeni, L., & Pasaribu, S. H. (2022). The Economy of Indonesia: Driven by Physical or Human Capital? *Jejak*, *15*(1), 10–28. https://doi.org/10.15294/jejak.v15i1.34418

Agussabti, A., Rahmaddiansyah, R., Hamid, A. H., Zakaria, Z., Munawar, A. A., & Abu Bakar, B. (2022). Farmers' perspectives on the adoption of smart farming technology to support food farming in Aceh Province, Indonesia. *Open Agriculture*, *7*(1), 857–870. https://doi.org/10.1515/opag-2022-0145

Ahumada, V. M. C., & Villarreal, C. C. (2019). Human capital formation and economic growth across the world: a pnel data econometric approach. *Economía Sociedad y Territorio*, *xx*, 25–54.

Akita, T., & Miyata, S. (2018). Spatial Inequalities in Indonesia, 1996–2010: A Hierarchical Decomposition Analysis. *Social Indicators Research*, *138*(3), 829–852. https://doi.org/10.1007/s11205-017-1694-1

Ali, M., Egbetokun, A., & Memon, M. H. (2018). Human capital, social capabilities and economic growth. *Economies*, *6*(1), 1–18. https://doi.org/10.3390/economies6010002

Amaluddin, A., Payapo, R. W., Laitupa, A. A., & Serang, M. R. (2018). A modified human development index and poverty in the villages of west seram regency, Maluku province, Indonesia. *International Journal of Economics and Financial Issues*, *8*(2), 325–330.

Anselin, L. (1988). Spatial Econometrics: Methods and Models. In *Spatial Econometrics: Methods and Models*. Kluwer Academic Publisher. https://doi.org/10.1111/j.1468-0262.2004.00558.x

Anselin, Luc. (2003). Spatial externalities, spatial multipliers, and spatial econometrics. *International Regional Science Review*, *26*(2), 153–166. https://doi.org/10.1177/0160017602250972

Anwar, A. (2017). Ketimpangan Spasial Pembangunan Ekonomi Dan Modal Manusia Di Pulau Jawa: Pendekatan Explatory Spatial

Data Analysis. *Asian Journal of Innovation and Entrepreneurship*, *2*(2), 90–109. https://doi.org/10.20885/ajie.vol2.iss2.art2

Anwar, A. (2018). Empirical Analysis of Human Capital Convergence in Indonesia. *Jejak*, *11*(2), 306–322. https://doi.org/10.15294/jejak.v11i2.16053

Aritenang, A. F., & Chandramidi, A. N. (2023). The spatial effects of fiscal decentralization on regional convergence: the case of regions in indonesia. *GeoJournal*, *88*(2), 2011–2030. https://doi.org/10.1007/s10708-022-10724-2

Aspiansyah, A., & Damayanti, A. (2019). Model Pertumbuhan Ekonomi Indonesia: Peranan Ketergantungan Spasial. *Jurnal Ekonomi Dan Pembangunan Indonesia*, *19*(1), 62–83. https://doi.org/10.21002/jepi.v19i1.810

Banerjee, A., Duflo, E., & Qian, N. (2020). On the Road: Access to Transportation Infrastructure and Economic Growth in China. *Journal of Development Economics*, 102442. https://doi.org/10.1016/j.jdeveco.2020.102442

Bangun, W. (2020). Employee production factor in economic development (a study in Indonesia). *Journal of Computational and Theoretical Nanoscience*, *17*(2–3), 859–863. https://doi.org/10.1166/jctn.2020.8731

Barro, R. J. (2001). Human Capital and Growth. *American Economic Review*, *91*(2), 12–17.

Barro, R. J., Caselli, F., & Lee, J. W. (2013). Symposium on human capital and economic development: An introduction. *Journal of Development Economics*, *104*, 181–183. https://doi.org/10.1016/j.jdeveco.2013.05.003

Bourgoin, M. A. S. (2014). A proposal for a modified Human Development Index. *CEPAL Review*, 29–44. https://doi.org/10.18356/ea3f94ea-en

BPS Statistics Indonesia. (2021). *Statistical Yearbook of Indonesia 2022*. BPS-Statistics Indonesia.

Brody, C., Harrison, N., & Yi, S. (2023). Income loss and gender-based violence during the COVID-19 pandemic among female entertainment workers in Cambodia: a cross-sectional phone survey. *BMC Public Health*, *23*(1). https://doi.org/10.1186/s12889-023-15044-9

Bucci, A., & Segre, G. (2011). Culture and human capital in a two-sector endogenous growth model. *Research in Economics*, *65*(4), 279–293. https://doi.org/https://doi.org/10.1016/j.rie.2010.11.006

Chen, P. P., & Gupta, R. (2009). An Investigation of Openness and Economic Growth Using Panel Estimation. *Indian Journal of Economics*, *89*, 355–483.

Dewanta, A. S., Santoso, R. P., & Anwar, A. (2017). Contribution of Human Capital In Economic Growth of A Regency / City. *Prosiding SNaPP2017 Sosial, Ekonomi, Dan Humaniora*, 500–509.

Dicker, D., Nguyen, G., Abate, D., Abate, K. H., Abay, S. M., Abbafati, C., Abbasi, N., Abbastabar, H., Abd-Allah, F., Abdela, J., Abdelalim, A., Abdel-Rahman, O., Abdi, A., Abdollahpour, I., Abdulkader, R. S., Abdurahman, A. A., Abebe, H. T., Abebe, M., Abebe, Z., … Murray, C. J. L. (2018). Global, regional, and national age-sex-specific mortality and life expectancy, 1950-2017: A systematic analysis for the Global Burden of Disease Study 2017. *The Lancet*, *392*(10159), 1684–1735. https://doi.org/10.1016/S0140-6736(18)31891-9

Diebolt, C., & Hippe, R. (2019). The long-run impact of human capital on innovation and economic development in the regions of Europe. *Applied Economics*, *51*(5), 542–563. https://doi.org/10.1080/00036846.2018.1495820

Elhorst, J. P. (2014). Spatial Econometrics From Cross-Sectional Data to Spatial Panels. In *SpringerBriefs in Regional Science*. Springer. https://doi.org/10.1007/978-3-642-40340-8_4

Gujarati, D. N. (2004). Basic Econometrics. In *The McGraw-Hill*.

Gunawan, A., Mendez, C., & Santos-Marquez, F. (2019). *Munich Personal RePEc Archive Regional Income Disparities , Distributional Convergence , and Spatial Effects : Evidence from Indonesia*. *97090*.

Hjazeen, H., Seraj, M., & Ozdeser, H. (2021). The nexus between the economic growth and unemployment in Jordan. *Future Business Journal*, *7*(1), 1–8. https://doi.org/10.1186/s43093-021-00088-3

Ismail, N. W., & Mahyideen, J. M. (2016). The Impact of Infrastructure on Trade and Economic Growth in Selected Economies in Asia. In *SSRN Electronic Journal* (Issue 553). https://doi.org/10.2139/ssrn.2709294

Jhingan, M. . (2012). *The Economics of Development and Planning* (4th ed.). Vrinda Publications (P),Ltd.

Jong-Wha Lee and Hanol Lee. (2018). HUMAN CAPITAL AND INCOME INEQUALITY. In *ADBI Working Paper Series*.

Kokuytseva, T., & Ovchinnikova, O. (2020). Theoretical aspects of human capital influence on regional development. *E3S Web of Conferences*, *217*, 1–9. https://doi.org/10.1051/e3sconf/202021707017

Leiwakabessy, E., & Amaluddin, A. (2020). A Modified Human Development Index, Democracy And Economic Growth In Indonesia. *Humanities & Social Sciences Reviews*, *8*(2), 732–743. https://doi.org/10.1016/S0305-750X(97)10063-8

LeSage, J., & Pace, R. K. (2009). Introduction to spatial econometrics. In *Introduction to Spatial Econometrics*. https://doi.org/10.1111/j.1467-985x.2010.00681_13.x

Liu, C., Tu, J., & He, Y. (2023). Measurement of China's Human Development Index and Analysis of Its Influencing Factors from the Perspective of New Development Concept. *Social Indicators Research*, *167*(1–3), 213–268. https://doi.org/10.1007/s11205-023-03105-w

Lucas, R. E. (1988). On the mechanics of economic development. *Journal of Monetary Economics*, *22*(1), 3–42. https://doi.org/10.1016/0304-3932(88)90168-7

Malau, A. G., & Sembiring, S. A. (2022). The Impact of The Labor Market, Regional Minimum Wages, Investment on The Economic Growth of The Tertier Sector in North Sumatra Province. *Quality - Access to Success*, *23*(191), 290–298. https://doi.org/10.47750/QAS/23.191.33

Márquez, M. A., Lasarte, E., & Lufin, M. (2019). The Role of Neighborhood in the Analysis of Spatial Economic Inequality. *Social Indicators Research*, *141*(1), 245–273. https://doi.org/10.1007/s11205-017-1814-y

Mejía, L. B. (2020). Mining and human capital accumulation: Evidence from the Colombian gold rush. *Journal of Development Economics*, *145*, 102471. https://doi.org/10.1016/j.jdeveco.2020.102471

Messakh, T. A., Rustiadi, E., Putri, E. I. K., & Fauzi, A. (2022). The Impact of Socioeconomic, Government Expenditure and Transportation Infrastructures on Economics Development: The Case of West Timor, Indonesia. *International Journal of Sustainable Development and Planning*, *17*(3), 971–979. https://doi.org/10.18280/ijsdp.170328

Mulyaningsih, T., Miranti, R., Daly, A., & Manning, C. (2019). Regional Skill Differentials: A Study of The Indonesian Labor Market. *Singapore Economic Review*. https://doi.org/10.1142/S0217590819500371

Munir, S., Elahi, I., & Khan, I. H. (2018). Impact of Human Capital and Infrastructure Development on Economic Growth in Pakistan. *European Journal of Economics, Finance and Administrative Sciences*, *7*(3), 127–140.

Nawir, D., Bakri, M. D., & Syarif, I. A. (2023). Central government role in road infrastructure development and economic growth in the form of future study: the case of Indonesia. *City, Territory and Architecture*, *10*(1). https://doi.org/10.1186/s40410-022-00188-9

Peck, J., Werner, M., & Jones, M. (2022). A dialogue on uneven development: a distinctly regional problem. *Regional Studies*, *0*(0), 1–12. https://doi.org/10.1080/00343404.2022.2116417

Pelinescu, E. (2015). The impact of human capital on economic growth. *Procedia Economics and Finance*, *22*, 184–190. https://doi.org/10.1016/S2212-5671(15)00258-0

Qu, X., & Lee, L. (2015). Estimating a spatial autoregressive model with an endogenous spatial weight matrix. *Journal of Econometrics*, *184*(2), 209–232. https://doi.org/https://doi.org/10.1016/j.jeconom.2014.08.008

Ragdad Cani, M., & Mendez, C. (2020). Human Development Dynamics across Districts of Indonesia: A Study of Regional Convergence and Spatial Approach. *SSRN Electronic Journal*, *100479*. https://doi.org/10.2139/ssrn.3596894

Rahman, M. M., Vu, X.-B. B., & Nghiem, S. (2022). Economic Growth in Six ASEAN Countries: Are Energy, Human Capital and Financial Development Playing Major Roles? *Sustainability (Switzerland)*, *14*(8). https://doi.org/10.3390/su14084540

Ray, D. (2010). Uneven growth: A framework for research in development economics. *Journal of Economic Perspectives*, *24*(3), 45–60. https://doi.org/10.1257/jep.24.3.45

Rey, S. J. (2001). Spatial empirics for economic growth and convergence. *Geographical Analysis*, *33*(3), 195–214. https://doi.org/10.1111/j.1538-4632.2001.tb00444.x

Ridha, M. R., & Budi, N. (2020). The Effect of Foreign Direct Investment, Human Development and Macroeconomic Condition on Economic Growth: Evidence from Indonesia. *Journal of Indonesian Applied Economics*, *8*(2), 46–54. https://doi.org/10.21776/ub.jiae.2020.008.02.5

Rizaldi, A., Muzwardi, A., Santoso, E., Iffan, M., & Fera, M. (2023). The Strategic Development of Maritime Connectivity In The Border Area In Indonesia. *Journal of Eastern European and Central Asian Research*, *10*(4), 701–711. https://doi.org/10.15549/jeecar.v10i4.1378

Romer, P. M. (1990). Endogenous technological change. *Journal of Political Economy*, *98*(5), S71–S102. https://doi.org/10.3386/w3210

Sharma, R. (2018). Health and economic growth: Evidence from dynamic panel data of 143 years. *PLOS ONE*, *13*(10), e0204940.

Sofilda, E., Zilal Hamzah, M., & Kusairi, S. (2023). Analysis of fiscal decentralisation, human development, and regional economic growth in indonesia. *Cogent Economics and Finance*, *11*(1). https://doi.org/10.1080/23322039.2023.2220520

Stillwell, J., & Clarke, G. (2006). Applied GIS and Spatial Analysis. In *Applied GIS and Spatial Analysis*. https://doi.org/10.1002/0470871334

Suparman, S., & Muzakir, M. (2023). Regional inequality, human capital, unemployment, and economic growth in Indonesia: Panel regression approach. *Cogent Economics and Finance*, *11*(2). https://doi.org/10.1080/23322039.2023.2251803

Tamura, R., Dwyer, J., Devereux, J., & Baier, S. (2019). Economic growth in the long run. *Journal of Development Economics*, *137*, 1–35. https://doi.org/10.1016/j.jdeveco.2018.10.010

Teixeira, A. A. C., & Queirós, A. S. S. (2016). Economic growth, human capital and structural change: A dynamic panel data analysis. *Research Policy*, *45*(8), 1636–1648. https://doi.org/https://doi.org/10.1016/j.respol.2016.04.006

Trimborn, T. (2018). On the analysis of endogenous growth models with a balanced growth path. *Journal of Mathematical Economics*, *79*, 40–50. https://doi.org/https://doi.org/10.1016/j.jmateco.2018.09.003

Utami, C. F., Mizuno, K., Hasibuan, H. S., & Budhi Soesilo, T. E. (2022). Discovering Spatial Development Control For Indonesia: A Systematic Literature Review. *Geography, Environment, Sustainability*, *15*(4), 64–79. https://doi.org/10.24057/2071-9388-2021-119

Vidyattama, Y. (2008). *Patterns of Provincial Economic Growth in Indonesia* (Issue January 2008).

Vidyattama, Y. (2013). Regional convergence and the role of the neighbourhood effect in decentralised Indonesia. *Bulletin of Indonesian Economic Studies*, *49*(2), 193–211. https://doi.org/10.1080/00074918.2013.809841

Vidyattama, Y. (2014). Issues In Applying Spatial Autocorrelation on Indonesia ' S Provincial Income Growth. *Australasian Journal of Regional Studies*, *20*(2), 375–402.

Wicaksono, E., Amir, H., & Nugroho, A. (2017). The sources of income inequality in Indonesia: A regression-based inequality decomposition. ADBI Working Paper. *Econstor*, *667*, 12.

Windhani, K., Mulyaningsih, T., & Hardoyono, F. (2022). Distribution of Human Capital Between Regions in Indonesia Using the Alternative Human Development Index. *KnE Social Sciences 2021 Annual Conference of Indonesian Association for Public Administration*, *2022*(4), 256–276. https://doi.org/10.18502/kss.v7i5.10554

Xu, Y., & Li, A. (2020). The relationship between innovative human capital and interprovincial economic growth based on panel data model and spatial econometrics. *Journal of Computational and Applied Mathematics*, *365*, 112381. https://doi.org/10.1016/j.cam.2019.112381

Yulianita, A., Susetyo, D., A.K, S., & Azwardi. (2017). Human Capital and Economic Convergence in Indonesia : An Empirical Analysis. *International Journal of Scientific and Research Publications*, *7*(7).