Analyzing the Influence of Gross Domestic Product on the Human Development Index Worldwide in 2021 Using a Nonparametric Regression Approach Based on Penalized Spline Estimator

Dita Amelia[1*], Azizah Atsariyyah Zhafira[2], Bryan Given Christiano Ginzel[3]
Fery Yulian Putra[4], and Yoga Setya Wibawa[5]

***Abstract*—People's welfare is a universal goal that is the main focus of all countries in the world. One of the indicators used to measure welfare is the Human Development Index (HDI), which includes education, health and per capita income. On the other hand, Gross Domestic Product (GDP) is the main measure of a region's economic growth. This research aims to highlight how regional economic dynamics affect human welfare in the world in 2021 and the data source was obtained from OurWorldInData. This research uses nonparametric regression with a penalized spline estimator approach. Penalized Spline analysis shows that the best model for predicting HDI based on GDP per capita is to use 2 knot points, namely $k1$=8000 and $k2$=50000. This model produces a Mean Squared Error (MSE) value of 0.0018 and Generalized Cross Validation (GCV) of 0.0019. In addition, this model has the ability to explain response variability of R^2=91.58%. The grouping of countries by GDP per capita reveals that economic improvement impacts human development differently across income levels. By tailoring strategies to specific income groups, policymakers can more effectively enhance human development outcomes, fostering a more equitable and prosperous society.**

Index Terms - Gross Domestic Product, Human Development Index, Penalized Spline Estimator.

I. INTRODUCTION

PEOPLE'S welfare is a universal goal and a primary focus for all countries worldwide. Susanti (2013) in Maryani [1] notes that the Human Development Index (HDI) is a strategic indicator widely used to evaluate the overall efforts and performance of development programs in a region. The HDI is crucial for assessing success in improving the quality of human life [2]. It encompasses education, health, and per capita income. Since 1990, the United Nations Development Program (UNDP) has used the HDI to evaluate human development achievements in various countries [3].

According to Alwi et al. [4] the HDI is a means for communities to access the results of development efforts. One indicator of a region's population welfare level is GDP per capita. According to Hadi Sasana [5] GRDP represents the net value of final goods and services produced by various economic activities in a region within a specific period.

The Central Bureau of Statistics explains that Gross Domestic Product (GDP) essentially includes the added value of goods and services produced by all business units over a certain period, or the total value of final goods and services produced by all economic sectors. An increase in the production of goods and services indicates economic growth, which is reflected in the Gross Domestic Product [6]. Rahardja and Manurung [7] noted that GDP calculation can provide an indication of a country's level of welfare.

The Human Development Index (HDI) and Gross Domestic Product (GDP) have been shown to be closely correlated in various studies. For instance, Arifah and Arifin [8] investigated the impact of Gross Regional Domestic Product (GRDP) on HDI in Central Java using multiple linear regression and found a positive relationship between GRDP and HDI. Similarly, Elistia and Syahzuni [9] assessed the effect of GRDP on HDI across 10 ASEAN countries with causal analysis, concluding that GRDP significantly influences HDI. Akbar and Prabowo [10] utilized the Granger Causality Test to reveal a significant bidirectional causality between GRDP and HDI in Indonesia. However, no prior research has explored the effect of GDP on HDI on a global scale using a penalized spline estimator. This research makes a significant contribution by exploring the relationship between GDP and HDI on a global scale through the application of a more flexible nonparametric approach. This method allows for more complex patterns between the variables to be revealed, which might not be captured by traditional parametric methods. In the context of an increasingly interconnected global development, it is crucial to understand how regional economic dynamics affect human well-being across countries. Such an understanding can help countries formulate more effective development policies, particularly in improving the quality of life for their populations. The novelty of this study lies in the use of a penalized spline estimator, which provides greater flexibility in modelling the non-linear relationship between GDP and HDI at the global level. This approach has not been widely explored in previous literature, offering a new perspective in the study of economic and human welfare relationships.

This study fills that gap by examining the global impact of

D. Amelia, A. A. Zhafira, B. G. C. Ginzel, F. Y. Putra, Y. S. Wibawa are with the Faculty Science and Technology, Department of Mathematics, Statistics Study Program, Universitas Airlangga, Surabaya 60115, Indonesia dita.amelia@fst.unair.ac.id
Manuscript received July 4, 2024; accepted March 12, 2025.

GDP on HDI, offering a novel contribution to the understanding of how regional economic dynamics influence human well-being worldwide. By employing nonparametric regression with a penalized spline estimator, this study benefits from increased flexibility in modelling the relationship between GDP and HDI. Unlike traditional parametric approaches, this method allows the data to define the shape of the regression curve, providing a more nuanced analysis of GDP's influence on HDI across different countries. The results of this study have the potential to impact both academic research and policy-making. In the academic field, it can enhance the understanding of non-linear relationships between economic growth and human development, thereby influencing future research methodologies. From a policy perspective, the findings could guide governments in designing more targeted economic policies aimed at improving human welfare, particularly in countries with varying levels of development. This can help ensure that economic growth translates more effectively into better living conditions for the population, thereby aligning economic policies with human development goals.

Using GDP as the primary measure of a region's economic growth and HDI as an indicator of human well-being encompassing education, health, and per capita income, this study emphasizes the impact of regional economic dynamics on human well-being. Previous research has shown that GDP significantly affects HDI in various regions, including ASEAN countries. This study aims to examine the effect of GDP on HDI on a global scale, comparing different countries to provide a broader understanding of GDP's influence on HDI levels worldwide. This study employs nonparametric regression with a penalized spline estimator approach. Nonparametric regression is chosen for its advantages over parametric regression, primarily its higher level of flexibility. This flexibility allows the data to determine the shape of the regression curve estimate independently, without being influenced by external factors from the researcher.

II. LITERATURE REVIEW

A. Gross Domestic Product (GDP)

Gross Domestic Product is the value that a country gives to its products and services [11]. According to the definition of Central Bureau of Statistics [12], Gross Domestic Product (GDP) is calculated as either the total added value of goods and services produced by all businesses within a specified period or the aggregate value of final goods and services across all economic sectors. It serves as a crucial metric for evaluating the economic well-being and performance of a country [13]. The growth of a country's GDP is influenced by the presence of capital sources, either from within or outside the country. GDP growth in developing countries can be done with foreign investment, if domestic investment increases [14].

B. Human Development Index (HDI)

The Human Development Index (HDI) summarizes average achievements in the key dimensions of human development: a long and healthy life, broadmindedness, and a decent standard of living. The United Nations Development Programme (UNDP) utilizes the HDI to measure a country's human development efforts, publishing it in the annual Human Development Report (HDR). The HDI is a composite index covering three fundamental areas of human development: (i) health sector: longevity; (ii) education sector: knowledge; and (iii) economic sector: decent living standards. The quality of human resources in a place can be seen from the human development index [15]. As stated by the UNDP in [16], the HDI is a benchmark for assessing human progress and examining the relationship between income and welfare.

C. Nonparametric Regression

Regression analysis is a statistical method used to explore and understand the relationship between response variables and predictor variables by identifying functional patterns. Nonparametric regression, on the other hand, is utilized when the specific form of the relationship between variables is not known. Nonparametric regression has the flexibility to find its own regression curve shape without being influenced by the subjectivity of the researcher [17]. The general nonparametric regression model can be expressed using the following equation;

$$y_i = g(x_i) + \varepsilon_i, \qquad i = 1, 2, \ldots, n \tag{1}$$

Here $g(x_i)$ represents the unknown regression function. function we want to estimate, and is the error term. To ascertain or predict the form of the regression function within nonparametric regression models, smoothing methods are employed. These techniques encompass approaches such as kernel smoothing, local linear regression, local polynomial regression, least squares splines, penalized splines, and Fourier series.

D. Penalized Spline Estimator

The specific smoothing method utilized to determine or estimate the regression function is referred to as the estimator [18]. In this study, we utilize the penalized spline estimator, which is a method within nonparametric regression known for producing smoother results compared to other estimators. This smoother outcome is achieved through its incorporation of parameters such as order, knot points, number of knot points, and a smoothing parameter (λ). The penalized spline estimator model form, if given n paired data $\{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}$ with response variable (y) and predictor variables (x) follows the regression model as follows [18] :

$$y_i = g(x_i) + \varepsilon_i, \qquad i = 1, 2, \ldots, n \tag{2}$$

Where $g(x_i)$ is estimated using a penalized spline estimator. The penalization helps avoid overfitting by adding a penalty term that controls the smoothness of the curve.

Given data points $\{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}$, the penalized spline estimator tries to minimize a loss function L , which balances the residuals between the observed and predicted values with a penalty term that controls the smoothness [19] :

$$L = (\boldsymbol{y} - \boldsymbol{X}\boldsymbol{\beta})^\top (\boldsymbol{y} - \boldsymbol{X}\boldsymbol{\beta}) + \lambda \boldsymbol{\beta}^\top \boldsymbol{D}\boldsymbol{\beta} \tag{3}$$

$\boldsymbol{y}$: Vector of observed values,
$\boldsymbol{X}$: Design matrix containing the predictors
$\boldsymbol{\beta}$: Vector of coefficients for the spline basis functions
λ : The smoothing parameter (also known as the regularization parameter), which controls the trade-off between the goodness of fit and smoothness. A larger imposes more penalty, making the curve smoother
$\boldsymbol{D}$: A diagonal matrix used in the penalty term. This controls the complexity of the model, typically related to the spline basis.

To find the optimal estimate for β , the derivate of L is taken and set to 0 [19] :

$$\frac{\partial L}{\partial \boldsymbol{\beta}} = 0 \Leftrightarrow -2\boldsymbol{X}^\top \boldsymbol{y} + 2\boldsymbol{X}^\top \boldsymbol{X}\boldsymbol{\beta} + 2\lambda \boldsymbol{D}\boldsymbol{\beta} = 0 \tag{4}$$

$$(\boldsymbol{X}^\top \boldsymbol{X} + \lambda \boldsymbol{D})\boldsymbol{\beta} = \boldsymbol{X}^\top \boldsymbol{y} \tag{5}$$

The solution for $\boldsymbol{\beta}$ is:

$$\widehat{\boldsymbol{\beta}} = (\boldsymbol{X}^\top \boldsymbol{X} + \lambda \boldsymbol{D})^{-1} \boldsymbol{X}^\top \boldsymbol{y} \tag{6}$$

Finally, the estimated regression function is:

$$\widehat{g}(x) = \boldsymbol{X}(\boldsymbol{X}^\top \boldsymbol{X} + \lambda \boldsymbol{D})^{-1} \boldsymbol{X}^\top \boldsymbol{y} \tag{7}$$

Performance Metrics: To evaluate the performance of the penalized spline model, several metrics are calculated [19] :

1) Calculate the Mean Square Error value (MSE(λ))
MSE measures the average squared difference between the observed data points and the predictions made by the model:

$$MSE(\lambda) = \frac{1}{n} \sum_{i=1}^{n} (y_i - \widehat{g}(x_i))^2 \tag{8}$$

A lower MSE value indicates better model performance
2) Calculate the Generalized Cross Validation value (GCV(λ))
GCV is a common method to select the optimal smoothing parameter λ. It balances the goodness of fit with model complexity and is computed as:

$$\text{GCV}(\lambda) = \frac{\text{MSE}(\lambda)}{(n^{-1}\text{tr}[\mathbf{I} - \mathbf{H}(\lambda)])^2} \tag{9}$$

Where $\mathbf{H}(\lambda)$ is the hat matrix, which describes how the model's predictions depend on the observed values. In regression, $\mathbf{H}(\lambda)$ is often represented as $\boldsymbol{X}(\boldsymbol{X}^T\boldsymbol{X} + \lambda\boldsymbol{D})^{-1}\boldsymbol{X}^T$, where $\boldsymbol{X}$ is the design matrix and λ is the smoothing parameter.
3) Calculate the coefficient of determination (R^2)
R^2 measures the proportion of variance in the observed data that is exoplained by the model. It is calculated as [20]:

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \widehat{y}_i)^2}{\sum_{i=1}^{k} (y_i - \overline{y})^2} \tag{10}$$

y_i : Value for observation i
$\widehat{y}_i$: Predicted value of y for observation i
$\overline{y}$: Mean of y value.
An R^2 close to 1 indicates that the model explains a large portion of the variance, while a lower value suggest that the model is not fitting the data well.

III. METHOD

A. Data Sources and Research Variables

The data utilized in this research are secondary data sourced from Our World in Data [21]. The dataset comprises global information, where the response variable is the Human Development Index (HDI), and the predictor variable is GDP per capita. There are 180 observations which are cross section data in the form of countries in 2021 managed by Our World in Data. The research variables used in this study are as follows:

TABLE I
RESEARCH VARIABLES

Variable	Description
GDP per - capita (x)	The sum of the value of all business units in a particular country divided by the population of that country.
HDI (y)	As an indicator to assess the overall effort and performance of development programs in a region.

B. Research Stages

The analysis is carried out using one of the nonparametric regression methods, namely Penalized Spline analysis using R software where the response variable y will be regressed on the predictor variable x. The steps to analyze HDI and GDP per capita data are as follows:

1) Inputting paired data of and variables for GDP per-capita and HDI.
2) Input the order, number of knots, and knot points which are smoothing parameters.
3) Estimate ($\widehat{g}(x)$)
4) Calculating the Mean Square Error value (MSE(λ))
5) Calculating the Generalized Cross Validation value (GCV(λ))
6) Calculating the coefficient of determination (R^2)
7) After the results of , MSE, GCV, and R^2 are obtained, determine the best polynomial order and number of knots that produce the minimum GCV by increasing the value of the order and number of knots. The parameter estimation results are used to determine the estimation model.
8) Analyze and interpret the results obtained from modeling HDI and GDP per capita data in the following way: Viewing the plot of estimation results against observations.
9) After obtaining the best model, the equation is decomposed based on knot points and interpreted

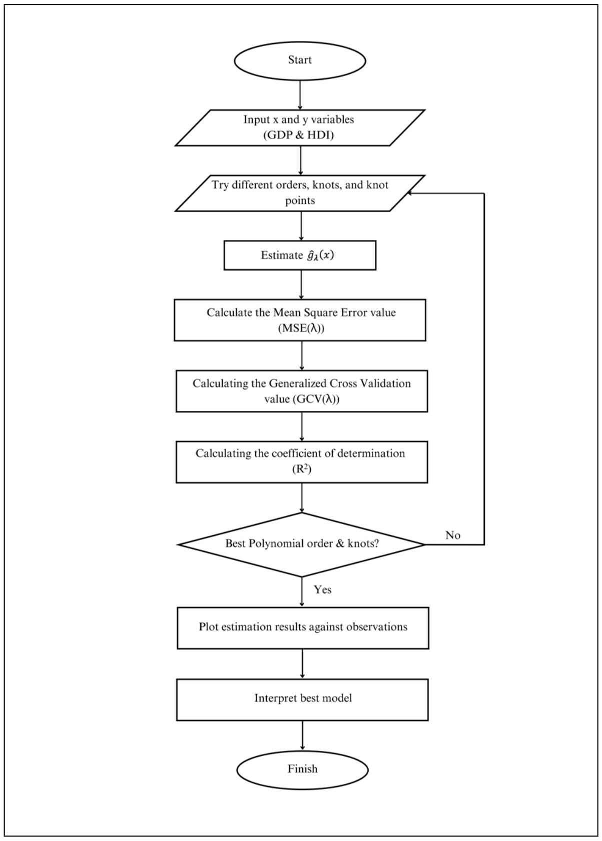

Fig. 1. Model Selection Flowchart

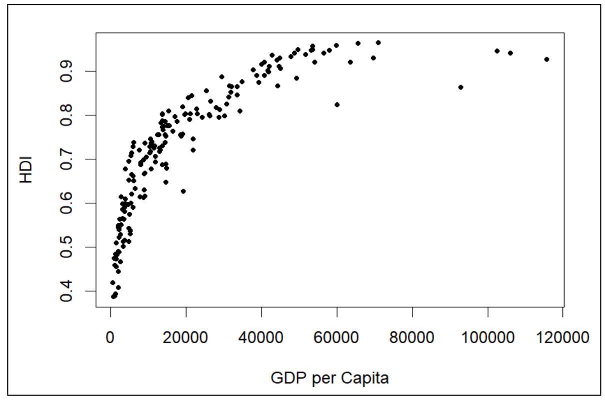

Fig. 2. Plot of GDP Per Capita against HDI of Countries in the World in 2021

IV. RESULT AND DISCUSSION

A. Data Description and Data Plot

The data used in this study are 180 countries in the world with GDP per capita as the predictor variable and HDI as the response variable. This study uses secondary data obtained from Our World in Data in 2021. The data description in this study is as follows:

TABLE II
DESCRIPTIVE STATISTICS

Variable	Mean	StDev	Min	Median	Max
GDP per-capita	20664	21353	705	13688	11568
HDI	0.723	0.1501	0.3870	0.7375	0.965

According to Table 2, the average GDP per capita globally is 20,664, while the HDI is 0.7239. The lowest GDP per capita with a value of 705 is in Burundi and the highest with a value of 115683 in Luxembourg. The lowest HDI is in Central African Republic with a value of 0.38780 and the highest is in Switzerland with a value of 0.9650.

The data plot between GDP Per Capita and HDI does not tend to form a certain pattern, therefore nonparametric regression analysis with a penalized spline approach is suitable for modeling in this study.

B. Penalized Spline Regression

In using the penalized spline estimator, it is necessary to select the smoothing parameter (λ), polynomial order, number of knots and knot location [18].

To obtain the minimum GCV, it is necessary to adjust the lambda interval with a suitable lambda increment. Knot points are selected iteratively until the minimum MSE, as well as optimal R^2 and λ , are achieved. Several knot and lambda values are tested to determine the best-fitting model. The selection of knot points is based on economic classifications. According to the World Bank's income classifications for 2024-2025 [22], a GDP per capita of 8,000 USD falls within the upper middle income category (4,516 to 14,004 USD), while 50,000 USD is firmly in the high income bracket (greater than 14,005 USD). Meanwhile, the lower and upper bounds, as well as the lambda increment, are adjusted to obtain the optimal lambda value. Below are fit measure results for each model.

TABLE III
MODEL FIT MEASURE

Knot	Knot Point	Model Fit Measure			Optimal λ
		GCV	MSE	R^2	
1	5000	0.0039	0.0038	0.8295	10
1	6000	0.0034	0.0033	0.8526	100
1	7000	0.0031	0.0030	0.8655	1000
1	8000	0.0030	0.0029	0.8683	10000
2	8000, 13000	0.0027	0.0027	0.8811	15000
2	**8000, 50000**	**0.0019**	**0.0018**	**0.9158**	**14890**

Analyzing GDP at these points helps to discern how economic transitions and extremes influence HDI. After several iterations, the best model was identified. Based on Table 3, the number of knots is limited to just two points to reduce model complexity and prevent overfitting. The knots are selected using a penalized spline method that exhibits different behaviour at the points 8,000 and 50,000, with a minimum GCV of 0.0019 and a minimum MSE of 0.0018. The GDP points of 8,000 and 50,000 USD are significant in understanding the relationship between economic wealth and human development, particularly in the context of the Human Development Index (HDI) and the World Bank's income classifications. At 8,000 USD, countries are transitioning from lower middle income to upper middle income, which can reveal significant changes in human development factors such as infrastructure, education, and health. On the other hand, 50,000 USD represents a high-income level where additional GDP may have diminishing returns on HDI. This level provides insights into how substantial economic resources impact human development at advanced stages. By examining these points, one can model the effects of GDP on HDI across a broad spectrum of economic contexts, capturing variations from mid-range to high income and evaluating the nuanced impact of economic growth on human development.

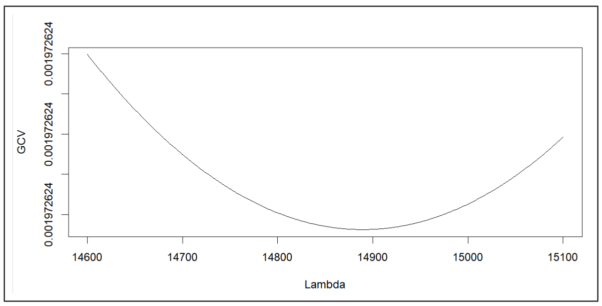

Fig. 3. Plot of GCV against Lambda

To determine the optimal lambda, appropriate lower and upper bounds for lambda are needed. In this study, the lower bound for lambda is set at 14,600 and the upper bound is 15,100, resulting in an optimal lambda of 14,890 with a lambda increment of 1. A large lambda value indicates that a significant penalty is applied to model complexity. This is typically done to prevent overfitting by reducing the spline's flexibility. In this context, a large lambda value means that a considerable penalty is imposed to keep the model simple and avoid excessive fitting to the training data. Therefore, we categorize three GDP per capita intervals that exhibit different characteristics of the HDI.

Thus, by choosing the best model estimation with polynomial order 1 and number of knots 2, the following parameter estimates are obtained:

TABLE IV
MODEL FIT MEASURE

Parameter	Value
β_0	0.4284718
β_1	3.471262×10^{-5}
β_2	-2.90165×10^{-5}
β_3	-6.129163×10^{-6}

Thus, the nonparametric regression equation can be written as follows:

$$\begin{aligned}\widehat{y} = {} & 0.4284728 + 3.471262 \times 10^{-5} x \\ & -2.90165 \times 10^{-5}(x-8000)_{+} - \\ & -6.129163 \times 10^{-6}(x-50000)_{+}\end{aligned} \tag{11}$$

The results of the above model estimation are depicted through the following plot:

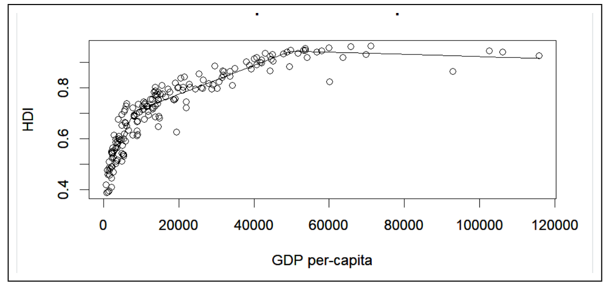

Fig. 4. Plot of GDP Per Capita against HDI of Countries in the World in 2021

After completing the previous calculation using penalized spline, three intervals were identified where the behaviour changes at the knot points 8000 and 50000. The intervals are ($x < 8000$), ($8000 \leq x < 50000$), and ($x \geq 50000$).

The increase in HDI for the GDP ($x < 8000$) interval shows a significant upward trend, indicating that as GDP per capita increases, the Human Development Index rises sharply because low Human Development needs must be met with limited GDP per capita. The increase in HDI for the GDP ($8000 \leq x < 50000$) interval shows a less significant rise, indicating that with a medium GDP, the HDI can increase but at a slower rate. The decline in HDI for GDP ($x \geq 50000$) indicates the possibility of issues in income distribution or the quality of public services not meeting the expectations associated with high GDP, which may lead to uneven improvements in quality of life.

C. Interpretation of the Optimal Regression Model

The optimal regression model can be written as follows.

$$\begin{aligned}\widehat{y} = {} & 0.4284728 + 3.471262 \times 10^{-5} \\ & -2.90165 \times 10^{-5}\,(x-8000)_{+} \\ & -6.129163 \times 10^{-6}(x-50000)_{+}\end{aligned} \tag{12}$$

The equation can be written as follows:

$$y = \begin{cases} 0.4284728 + 3.471262 \times 10^{-5} x, for\, x < 8000 \\ 0.6606048 + 5.60512 \times 10^{-6} x, for\, 8000 \leq x < 50000 \\ 0.96706295 - 4.24043 \times 10^{-7}, for\, x \geq 50000 \end{cases}$$

The model can be interpreted as follows.

- If GDP per capita is less than 8000, then every 1000 USD increase in GDP per capita results in an increase in HDI of 0.03471262 units.
- If GDP per capita is between 8000 and less than 50000, then every 1000 USD increase in GDP per capita results in an increase in HDI of 0.00560512 units.
- If GDP per-capita is greater than 50000, then every 1000 USD increase in GDP per-capita results in a decrease in HDI by 0.000424043 units.

D. Country Grouping based on Knot Intervals

In this study, there are 180 countries in the world grouped into 3 groups, each group is at a certain interval and changes behaviour at two knot points, namely at points 8000 and 50000. These three groups are categorized into three categories, namely low GDP per capita ($x < 8000$), medium GDP per capita ($8000 \leq x < 50000$), and high GDP per capita ($x \geq 50000$). The following is an analysis of country groupings based on GDP per-capita interval groups.

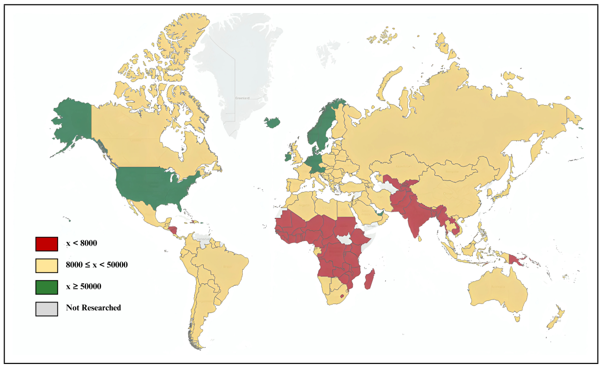

Fig. 5. Mapping GDP Per Capita Intervals and Their Impact on HDI

TABLE V
COUNTRY GROUPING INTERVAL $x < 8000$

$\hat{y} = 0.4284728 + 3.471262 \times 10^{-5}x$	
Country	**Analysis**
Central African Republic, Niger, Chad, Mali, Burundi, Burkina Faso, Sierra Leone, Mozambique, Guinea, Afghanistan, Democratic Republic of Congo, Guinea-Bissau, Madagascar, Liberia, Ethiopia, Gambia, Benin, Malawi, Djibouti, Senegal, Sudan, Lesotho, Tanzania, Cote d'Ivoire, Pakistan, Mauritania, Rwanda, Nigeria, Uganda, Togo, Zimbabwe, Haiti, Papua New Guinea, Solomon Islands, Zambia, East Timor, Cameroon, Comoros, Angola, Nepal, Kenya, Cambodia, Congo, Myanmar, Ghana, Sao Tome and Principe, Vanuatu, Laos, Honduras, India, Cape Verde, Tuvalu, Bangladesh, Nicaragua, Tajikistan, Kyrgyzstan, Samoa, Palestine, Uzbekistan, Marshall Islands, Tonga.	An increase in per-capita GDP results in a notable improvement in HDI. Globally, there are approximately 1,650 million individuals living in impoverished conditions characterized by low life expectancy and limited access to education and healthcare services [23]. Long-term vulnerability poses a significant challenge to social development. Addressing the root causes of these disadvantages can enable broader participation in progress, promoting greater equity and sustainability in social development efforts [23]. Notably, countries in the Low Human Development group have experienced the highest increase in HDI [23].

TABLE VI
COUNTRY GROUPING INTERVAL $8000 \leq x < 50000$

$\hat{y} = 0.6606048x + 5.60512 \times 10^{-6}$	
Country	**Analysis**
Eswatini, Namibia, Kiribati, Guatemala, Equatorial Guinea, Iraq, El Salvador, Bhutan, Botswana, Gabon, Morocco, Suriname, Bolivia, Philippines, Nauru, Belize, Jamaica, Indonesia, Fiji, Saint Lucia, Vietnam, Guyana, South Africa, Lebanon, Egypt, Tunisia, Paraguay, Mongolia, Jordan, Dominica, Azerbaijan, Algeria, Libya, Ecuador, Colombia, Maldives, Ukraine, Peru, Dominican Republic, Brazil, Mexico, North Macedonia, Moldova, Saint Vincent and the Grenadines, Armenia, Bosnia and Herzegovina, Iran, Sri Lanka, China, Albania, Grenada, Mauritius, Seychelles, Bulgaria, Thailand, Malaysia, Bahamas, Kazakhstan, Belarus, Palau, Barbados, Trinidad and Tobago, Costa Rica, Serbia, Georgia, Oman, Panama, Uruguay, Russia, Saint Kitts and Nevis, Antigua and Barbuda, Romania, Montenegro, Turkey, Argentina, Hungary, Slovakia, Chile, Portugal, Latvia, Saudi Arabia, Croatia, Lithuania, Poland, Bahrain, Greece, Estonia, Czechia, Italy, Cyprus, Spain, France, Israel, Malta, Slovenia, Japan, South Korea, United Kingdom, Canada, New Zealand, Finland, Australia.	An increase in GDP per capita within a certain range brings about a focus on reducing economic inequality, efficient use of resources and improving quality of life. Even if additional allocations for basic services are made, the increase in HDI may be limited as basic needs are met and resources are used more efficiently. As Western Balkan countries such as Serbia, Albania, Macedonia, and Bosnia and Herzegovina, which have middle incomes, experience greater income inequality than inequality in education and life expectancy [23]. Therefore, an additional increase in GDP per capita does not result in a significant increase in the Human Development Index (HDI) in countries in this group.

TABLE VII
COUNTRY GROUPING INTERVAL $x \geq 50000$

$\hat{y} = 0.96706295 - 4.24043 \times 10^{-7}x$	
Country	**Analysis**
Brunei, Qatar, Austria, United States, Luxembourg, United Arab Emirates, Belgium, Netherlands, Singapore, Ireland, Denmark, Germany, Sweden, Iceland, Hong Kong, Norway, Switzerland.	HDI in groups with high numbers tends to be slow due to the convergence theory, where growth reaches its maximum point so that the increase slows down. The effect of GDP per capita also does not directly increase the HDI value as the index is constructed from various indicators. The concept of the law of diminishing returns in economics states that when GDP per-capita is high, additional wealth tends to provide less and less benefit to people's welfare. This is because economic inequality allows the distribution of funds to favor the rich, while the incremental benefits from additional consumption tend to decrease. Thus, despite an increase in GDP per capita, the impact on people's welfare is insignificant. For example, Qatar has the highest GNI but ranks 37th in HDI due to factors such as rapid utilization of natural resources that is not matched by adequate improvements in education and life expectancy, which take time to significantly improve [23].

V. CONCLUSIONS

The results of this analysis produced three interval groups based on GDP per capita, with two knots placed at 8000 USD and 50000 USD. The grouping of countries by GDP per-capita shows that economic improvement has a different impact on human development. Countries with an income below 8,000 USD should concentrate on improving basic services such as education and health, developing essential infrastructure, and providing social assistance to enhance quality of life and welfare. For those with an income between 8,000 and 50,000 USD, the focus should shift towards reducing economic inequality through equitable development, optimizing budget allocation, and enhancing quality of life aspects like mental health, gender equality, and education to build a skilled workforce. In countries with an income above 50,000 USD, efforts should be directed at ensuring a fair distribution of wealth to mitigate economic inequality, while also investing in social and cultural development to further elevate the overall quality of life and social welfare. In summary, this study underscores the complex relationship between GDP per capita and HDI, revealing that economic growth impacts human development differently across various income levels. It emphasizes the need for targeted policy approaches based on income intervals to effectively address the distinct challenges and opportunities faced by countries at different stages of economic development. By tailoring strategies to specific income groups, policymakers can better enhance human development outcomes and ensure a more equitable and prosperous society.

ACKNOWLEDGMENT

The authors would like to thank the Statistics Study Program, Faculty of Science and Technology, Universitas Airlangga, for the support and funding of this research.

REFERENCES

[1] E. Maryani, Mahmud, and H. Gusvita, "Analisis Tingkat Kemiskinan dan Indeks Pembangunan Manusia (IPM) Kabupaten/Kota di Provinsi Sumatera Barat," *J. Res. Ilmu Pertan.*, vol. 2, no. 2, pp. 165–172, 2022, [Online]. Available: https://ejurnal-unespadang.ac.id/index.php/JRIP/article/view/622%0Ahttps://ejurnal-unespadang.ac.id/index.php/JRIP/article/download/622/609

[2] T. M. Sapaat, A. L. C. P. Lapian, and S. Y. L. Tumangkeng, "Analisis Faktor-Faktor Yang Mempengaruhi Indeks Pembangunan Manusia Di Provinsi Sulawesi Utara Tahun (2005-2019)," *J. Berk. Ilm. Efisiensi*, vol. 20, no. 03, pp. 45–56, 2020.

[3] M. Hopkins, "Human Development Revisited " A New UNDP Report," *World Dev.*, vol. 19, no. 10, pp. 1469–1473, 1991.

[4] W. Alwi, M. Irwan, and M. Musfirah, "Penerapan Regresi Nonparametrik Spline Dalam Memodelkan Faktor-Faktor Yang Mempengaruhi Indeks Pembangunan Manusia (Ipm) Di Indonesia Tahun 2018," *J. MSA (Mat. dan Stat. serta Apl.)*, vol. 9, no. 2, 2021, doi: 10.24252/msa.v9i2.23055.

[5] H. Sasana, "Analisis Dampak Transfer Pemerintah Terhadap Kinerja Fiskal Di Kabupaten/Kota Propinsi Jawa Tengah Dalam Pelaksanaan Desentralisasi Fiskal," *Jurnal Ekonomi Pembangunan: Kajian Masalah Ekonomi dan Pembangunan*, vol. 7, no. 2. p. 223, 2007. doi: 10.23917/jep.v7i2.3985.

[6] D. Silitonga, "Pengaruh Inflasi Terhadap Produk Domestik Bruto (Pdb) Indonesia Pada Periode Tahun 2010-2020," *ESENSI J. Manaj. Bisnis*, vol. 24, no. 1, p. 2021, 2021.

[7] P. Rahardja and M. Manurung, *Teori Ekonomi Makro; Suatu Pengantar*, Keempat. Jakarta: :Lembaga Penerbit Fakultas Ekonomi Universitas Indonesia, 2008.

[8] D. C. Arifah and A. Arifin, "Analysis The Effect of Gross Regional Domestic Product (GRDP) Per Capita , Government Expenditures in Education and Health on Human Development Index on Central Java Period 2019-2021," *Int. J. Bus. Manag. Technol.*, vol. 6, no. 6, pp. 379–386, 2022.

[9] Elistia and B. A. Syahzuni, "the Correlation of the Human Development Index (Hdi) Towards Economic Growth (Gdp Per Capita) in 10 Asean Member Countries," *J. Humanit. Soc. Stud.*, vol. 02, no. 02, pp. 40–46, 2018, [Online]. Available: https://journal.unpak.ac.id/index.php/jhss

[10]] A. M. Akbar and P. S. Prabowo, "Hubungan Kausalitas Produk Domestik Regional Bruto, Indeks Pembangunan Manusia Dan Kemiskinan Di Indonesia," *Indep. J. Econ.*, vol. 3, no. 2023, pp. 138–149, 2023, [Online]. Available: https://ejournal.unesa.ac.id/index.php/independent

[11] Y. T. Cahyani, "Pengaruh Inflasi, Suku Bunga (BI Rate), Produk Domestik Bruto (PDB) Terhadap ROA (Studi Pada Bank Pembiayaan Rakyat Syariah (BPRS) di Indonesia Tahun 2009-2016)," *IQTISHADIA J. Ekon. Perbank. Syariah*, vol. 5, no. 1, pp. 58–83, 2018, doi: 10.19105/iqtishadia.v5i1.1695.

[12] Badan Pusat Statistik, "Produk Domestik Bruto," 2024.

[13] Jojo, A. Gandhy, E. S. Simanullang, and A. Frasipa, "Analisis Human Capital Terhadap Pertumbuhan Ekonomi Indonesia," *JIM UPB*, vol. 7, no. 2, pp. 170–180, 2019, [Online]. Available: http://ejournal.upbatam.ac.id/index.php/jim/article/view/1001

[14] Alice, Ekklesia, L. Sepriani, and Yohana Juwitasari Hulu, "Pengaruh Investasi Penanaman Modal Terhadap Pertumbuhan Ekonomi Melalui Peningkatan Produk Domestik Bruto di Indonesia," *WACANA Ekon. (Jurnal Ekon. Bisnis dan Akuntansi)*, vol. 20, no. 2, pp. 77–83, 2021, doi: 10.22225/we.20.2.2021.77-83.

[15] M. Fuady, M. R. F. Fuady, and F. Aulia, "Kemiskinan Multi Dimensi dan Indeks Pembangunan Manusia di Indonesia," *Tataloka*, vol. 24, no. 4, pp. 330–337, 2022, doi: 10.14710/tataloka.24.4.330-337.

[16] N. Nasruddin and A. Azizah, N., "Analisis Indeks Pembangunan Manusia (IPM) di Negara ASEAN," *J. Geogr. (Geografi Lingkung. Lahan Basah)*, vol. 3, no. 1, p. 45, 2022, doi: 10.20527/jgp.v3i1.503.

[17] A. T. R. Dani, L. Ni'matuzzahroh, V. Ratnasari, and I. N. Budiantara, "Pemodelan Regresi Nonparametrik Spline Truncated pada Data Longitudinal," *Inferensi*, vol. 4, no. 1, p. 47, 2021, doi: 10.12962/j27213862.v4i1.8737.

[18] N. Chamidah and B. Lestari, *Analisis Regresi Nonparametrik dengan Perangkat Lunak R*. Airlangga University Press, 2022.

[19] N. Chamidah, M. Rifada, and D. Amelia, “a Theoretical Discussion on Modeling the Number of Covid-19 Death Cases Using Penalized Spline Negative Binomial Regression Approach,” *Commun. Math. Biol. Neurosci.*, vol. 2022, pp. 1–14, 2022, doi: 10.28919/cmbn/7518.

[20] K. Taira, D. McInnes, and L. Zhang, “How many data points and how large an R-squared value is essential for Arrhenius plots?,” *J. Catal.*, vol. 419, pp. 26–36, 2023, doi: 10.1016/j.jcat.2023.01.033.

[21] Our World in Data, “GNI per capita vs. GDP per capita,” England and Wales, 2021.

[22] E. Metreau, K. E. Young, and S. G. Eapen, “World Bank country classifications by income level for 2024-2025,” 2024. [Online]. Available: https://blogs.worldbank.org/en/opendata/world-bank-country-classifications-by-income-level-for-2024-2025

[23] B. Dasic *et al.*, “Human development index in a context of human development: Review on the western Balkans countries,” *Brain Behav.*, vol. 10, no. 9, 2020, doi: 10.1002/brb3.1755.