JTAM (Jurnal Teori dan Aplikasi Matematika)
http://journal.ummat.ac.id/index.php/jtam
p-ISSN 2597-7512 | e-ISSN 2614-1175
Vol. 9, No. 3, July 2025, pp. 898-918

Modeling the Human Development Index of the West Nusa Tenggara Province using Panel Data Regression

Alfira Mulya Astuti[1*], Pizatul Islamiyah[1], Achmad Syahrul Choir[2], Mohd Afifi Bahurudin Setambah[3]
[1]Mathematics Education Study Program, Universitas Islam Negeri Mataram, Mataram, Indonesia
[2]Statistical Computing Study Program, Politeknik Statistika STIS, Jakarta, Indonesia
[3]Department of Educational Studies, Universiti Pendidikan Sultan Idris, Tanjong Malim, Malaysia
alfiramulyastuti@uinmataram.ac.id

Article History:
Received : 02-05-2025
Revised : 25-06-2025
Accepted : 26-06-2025
Online : 03-07-2025

Keywords:
Regression Analysis;
Panel Model;
Human Development Index.

ABSTRACT

The human development index is the primary indicator used to measure the level of success of human development. It is important to study because the human development index can provide a more comprehensive picture of a region or country's progress in improving its people's quality of life and guide the government in designing more effective development policies, identifying social gaps, and directing efforts to improve the quality of life of society as a whole. This research aims to identify the most significant component of the HDI calculation through the application of standardized coefficients and to analyze the influence of the number of poor people on the human development index in West Nusa Tenggara (NTB) province during 2010-2023 period. This research is quantitative in essence. The independent variables were life expectancy at birth, expected years of schooling, mean years of schooling, adjusted per capita expenditure, and number of poor people. The individual observation units in this study were 10 districts/cities in the NTB province. Data were sourced from Badan Pusat Statistik (BPS) NTB Province and analyzed using the panel regression method. The results of model selection show that the Fixed Effect Model is the best model for modeling the human development index in NTB province. The adjusted per capita expenditure had the greatest impact on the human development index of NTB Province in 2010–2023. The expected years of schooling was the variable that contributed the least to the entire components of the HDI in NTB province. The number of poor people had a significant effect on the human development index of NTB province from 2010 to 2023.

https://doi.org/10.31764/jtam.v9i3.31055

A. INTRODUCTION

Development refers to a nation's or region's endeavor to enhance the welfare and quality of life of its populace (Lind, 2019; Sari, 2022). Prior to 1990, development was predominantly assessed through economic measures, including economic growth and per capita income. This strategy frequently overlooks the distribution of welfare and the community's quality of life (BPS-Statistics Indonesia, 2025). In the current era of globalization, Indonesia, as a developing nation, is initiating a development paradigm that prioritizes sustainable and inclusive human advancement. The objective of the human development strategy is to assist nations in attaining sustainable development goals by the fortification of policy-making, leadership, partnerships, and institutional capacity, alongside the enhancement of resilience (Tobaigy et al., 2023). A key indicator of developmental achievement in a country or region is the availability of high-quality human resources. Effective human resources are evidenced by enhancements in educational attainment, healthcare services, and economic development (Pramesti & Indrasetianingsih, 2018). Skilled human resources are pivotal to community development. The growth of communities depends on the active engagement and empowerment of individuals, cultivating a sense of ownership and accountability among citizens. Investing in great human resources enables governments to develop competent workers that provide new solutions and propel advancement across all areas.

The United Nations Development Program (UNDP) establishes four main human development elements: equity, productivity, empowerment, and sustainability. Human development, defined as "a process of enlarging people's choices", involves stages or processes to improve human living standards (UNDP, 2022). Human development is an indicator that needs attention because high economic growth cannot always solve welfare problems such as poverty and the standard of living of society at large. Measuring human development progress refers to a method developed or popularized by the UNDP: the Human Development Index or HDI (Jalil & Kamaruddin, 2018; Mangaraj & Aparajita, 2020; Yolanda, 2017).

BPS-Statistics Indonesia (2024) defines HDI is a statistical measure used to measure the progress and quality of life of people in a country or region based on three indicators: health, education and decent living standards. The health dimension is assessed via life expectancy, the education dimension is evaluated through the mean years of schooling and expected years of schooling, whereas the decent standard of living dimension is quantified by per capita income, typically Gross National Income (GNI) per capita adjusted for Purchasing Power Parity (Herre & Arriagada, 2023). By considering these indicators, HDI can provide a more comprehensive picture of a country's progress in improving the quality of life of its people. HDI can guide governments in designing more effective development policies, identifying social gaps, and directing efforts to improve the overall quality of life. Furthermore, the HDI can elucidate disparities in human development outcomes among locations with comparable per capita incomes (Purba, 2019).

BPS-Statistics NTB Province (2023) stated that the HDI in West Nusa Tenggara (NTB) province tends to increase. Even though there is an increase every year, the HDI of NTB province is still 29th out of 34 provinces, which shows that NTB province is in the category of the six lowest provinces in Indonesia in 2023. Therefore, the researchers were interested in further examining the factors influencing HDI in NTB province. The components of calculating the HDI are: life expectancy at birth to measure health indicators, literacy rate and average years of schooling to measure knowledge indicators, and per capita expenditure as a benchmark indicator of a decent standard of living. Futhermore, the study of HDI has evolved alongside advancements in related fields. Other factors (variables) form the basis of HDI calculations.

Several previous researchers have studied HDI in various regions in Indonesia. Humaira & Nugraha (2018) conducted the factors affecting the HDI in West Kalimantan province. The results of their research showed that gross regional domestic product at constant price, adjusted per capita expenditure, expected years of schooling, mean years of schooling, and life expectancy at birth significantly affect HDI in West Kalimantan province. Yanuar et al. (2018) investigated HDI in North Sumatera province. The total expenditure per capita per month and mean years of schooling influence HDI in North Sumatera province. Pramesti & Suharsono (2019) and Anekawati et al. (2024) studied HDI in East Java province. The expected years of schooling significantly affect HDI in East Java province. Rahmawati et al. (2021) and Saputro et al. (2021) examined the modeling of HDI in Papua province. The research results showed that the factors significantly influencing HDI in Papua province are the population growth rate, percentage of poor population, and economic growth. Pertiwi et al. (2023) compared HDI in Papua and West Sumatera province. The research results showed that mean years of schooling influence HDI in Papua and West Sumatera province. Kamil et al. (2024) studied HDI in Indonesia. The health complaints was the most influential predictor on HDI. Susanti et al. (2025) analyzed HDI in Indonesia. The life expectancy at birth, mean years of schooling, and per capita expenditures significantly affect the HDI in Indonesia

The results of previous research show that there are several variables from the health, education, and economic sectors that are widely used by previous researchers and have a significant effect on HDI, namely; life expectancy at birth, expected years of schooling, mean years of schooling, and per capita expenditure are adjusted. Life expectancy represents the health sector, expected years of schooling and average years of schooling represent the education sector, and adjusted per capita expenditure represents the economic sector. Therefore, in this study, researchers used life expectancy, expected years of schooling, average years of schooling, and adjusted per capita expenditure as independent variables to model the HDI. Another variable from the economic sector that influences HDI is the number of poor people. The community's limitations in meeting basic needs, such as food, clothing and shelter, are shown by the indicator of the number of poor people. Thus, it is hoped that the decrease in the number of poor people will be able to increase the HDI (Dewi & Nurhayati, 2023). Therefore, the number of poor people is used as an additional independent variable to model HDI. In addition, the selection of independent variables is adjusted to data availability. Consequently, this study uses life expectancy at birth, expected years of schooling, average years of schooling, adjusted per capita expenditure, and the number of poor people to model the HDI in NTB province.

The HDI in NTB province has been investigated by several researcher. Wathani et al. (2017) studied the HDI in NTB with partial least square method. Rayes (2019) observed the NTB's HDI used panel regression for 2013-2017 period. Nur & Yuliansyah (2020) examined the HDI of NTB utilized multiple regression technique. Sapurah et al. (2021) investigated the HDI in NTB applied fixed effect model on panel regression during 2010-2017. Pramuja et al., (2023) analyzed the HDI in NTB province from 2016 to 2020 using the first difference generalized method of moment (FDGMM). Astuti, Afifurrahman, et al. (2024) evaluated HDI of NTB by spatial panel model from 2010-2022. Prior scholars examining HDI in NTB predominantly employed the panel regression methodology. This is because the number of districts/cities in the NTB province is relatively small and resulting in problems estimating parameters related to degrees of freedom. According to Lee & Yu (2015), Belotti et al. (2017), Gallo & Pirotte (2017), Astuti et al. (2020, 2021, 2023), and Astuti, Ashri, et al. (2024), panel data regression is superior to studying dynamic changes by recognizing and measuring effects more accurately than regression limited to time series or cross-section data. Panel data provides more informative information with more degrees of freedom, lower correlation between variables, and higher efficiency. Thus, in this research, panel data regression is used to model HDI in the NTB province.

The primary distinction between this study and prior researches resides in the observation duration, independent variables, and interpretation of regression outcomes. The observation period variable utilized in this research spans from 2010 to 2023. The independent variables include mean years of schooling, expected years of schooling, life expectancy at birth, adjusted per capita expenditure, and the number of poor people. The independent variables employed in this study mainly consist of the elements that form the HDI. Consequently, the interpretation of the regression model employs the relative contributions of the independent variables, excluding the number of poor people. This research seeks to identify the most significant component of the HDI calculation through the application of standardized coefficients and to analyze the influence of the number of poor people on the HDI of NTB Province in 2010-2023.

B. METHODS

1. Research Variable

The research variables used to model the human development index in NTB province are presented in Table 1.

Table 1. Research Variables

Variable	Unit	Notation
Human development index (HDI)	Percent	Y
Life expectancy at birth (LEB)	Year	X_1
Expected years of schooling (EYS)	Year	X_2
Mean years of schooling (MYS)	Year	X_3
Adjusted per capita expenditure (APE)	IDR Thousand	X_4
Number of poor people (NPP)	Persons	X_5

2. Types, Sources, and Techniques of Data Collection

The data used in this research is secondary data obtained from BPS of NTB Province website with a panel data structure. The time series unit starts from 2010 to 2023, and the cross-section unit consists of 10 districts/cities in the NTB province, namely: Lombok Barat District, Lombok Timur District, Lombok Tengah District, Lombok Utara District, Sumbawa District, Sumbawa Barat district, Bima district, Dompu district, Bima city and Mataram city. The data collection technique in this research is documentation.

3. Data Analysis Technique

The data analysis technique used in this research is panel data regression analysis. This subpoint discusses panel data regression and the assumption tests used.

a. Definition and Concept of Panel Data Regression

Panel data regression is a regression that uses panel data, namely combined data between cross-section data and time series data (Baltagi, 2021). Cross-section data can be individuals, households, companies, countries, or other entities observed at a specific time. Time series data can be daily, weekly, monthly, quarterly, annually, or at other time intervals. Panel data regression uses data from observations of cross-section units repeatedly over several periods (Astuti et al., 2023). The panel data regression model can be seen in equation (1).

$$Y_{it} = \beta_0 + \beta_1 X_{1\,it} + \beta_2 X_{2it} + \cdots + \beta_K X_{Kit} + \varepsilon_{it} \quad (1)$$

where Y_{it} is dependent variable at the i-th observation unit and time-t with $i = 1,2,\dots,N$ and $t = 1,2,\dots,T$; β_0 is constant/intercept, β_k is parameter for the k-th variable with $k = 1,2,\dots,K$, X_{kit} is k-th independent variable of the i-th individual at time-t, i is unit cross section, t is unit time series, and ε_{it} is error at the i-th observation unit and time-t.

b. Approach and Estimation in Panel Data Regression Models

In panel data regression, there are three estimation methods, namely: the Common Effect Model or CEM, Fixed Effect Model or FEM, and Random Effect Model or REM (Wooldridge, 2016).

1) Common Effect Model (CEM)

The CEM model is the most straightforward technique for estimating panel data because it only combines time series and cross-section data. This model ignores individual or time dimensions so it is assumed that individual behavior is the same over various periods. This model can be estimated using the Ordinary Least Squares or OLS approach (Greene, 2018). The CEM model is written in equation (2).

$$Y_{it} = \beta_0 + \beta_k X_{kit} + \varepsilon_{it} \quad (2)$$

The symbol definitions in equation (2) are identical to those in equation (1).

2) Fixed Effect Model (FEM)

This model is used to overcome the weaknesses of CEM. FEM shows constant differences between objects, even with the same regressor coefficients. FEM is a model that assumes that the intercept coefficient is different for each individual. In FEM, dummy variables are used to explain the intercept coefficient for each individual. To estimate this FEM, the Least Square Dummy Variable method is used. FEM is written in equation (3).

$$Y_{it} = \beta_0 + \mu_i + \beta_k X_{kit} + \varepsilon_{it} \quad (3)$$

where μ_i is effect of the i-th individual (dummy variable) and the other symbol definitions in equation (3) are identical to those in equation (1).

3) Random Effect Model (REM)

This model accounts for unobserved heterogenity across individuals and/or time by modeling the error term as having specific components (e.g., individual-specific effects, time-specific effects). The advantage of using this model is that it can eliminate heteroscedasticity. This model is called the Error Component Model (ECM) or Generalized Least Square or GLS. REM can be seen in equation (4).

$$Y_{it} = \beta_0 + \beta_k X_{kit} + \varepsilon_{it};\ \varepsilon_{it} = u_i + V_t + W_{it} \quad (4)$$

where u_i is cross section error component, V_t is time series error component, W_{it} is combined error component, and the other symbol definitions in equation (4) are identical to those in equation (1).

c. Selection of Panel Models

The panel data regression model selection test aims to determine the model that will be used, whether it is CEM, FEM, or REM (Astuti, Ashri, et al., 2024). Selection of a panel data regression model can be done through a series of tests, including:

1) Chow Test

The Chow test is used to choose between CEM and FEM through the residual sum squares value. The testing procedure is as follows:

Hypothesis:

H_0: Common Effect Model (CEM)

H_1: Fixed Effect Model (FEM)

The test statistic used is the F-test, which can be seen in equation (5).

$$F_{Test} = \frac{[RRSS - URSS]/(N-1)}{URSS/(NT-N-K)} \quad (5)$$

where N is the number of individuals (cross section), T is the number of periods (time series), K is the number of independent variables, *RRSS* is restricted residual sums of squares, and *URRS* is unrestricted residual sums of squares.

Decision:

- If p-value ≤ α (significance value), then the initial hypothesis (H_0) is rejected, which means that the selected model is FEM.
- If the p-value > α, then H_0 is not rejected, which means that the selected model is CEM

2) Hausman Test

This test is used to choose between REM or FEM. Assumptions regarding the correlation between the residual components and the independent variables can be made to determine the Random Effect Model. If it is assumed that there is no correlation between the residuals and the independent variables, then the appropriate model is REM. If otherwise, then the proper model is FEM.

Hypothesis:

H_0: Random Effect Model (REM)

H_1: Fixed Effect Model (FEM)

The statistical test used is the Chi-square test (χ^2) based on Wald criteria, which can be seen in equation (6).

$$W = \hat{q}'[var\ (\hat{q}')]^{-1}\hat{q}' = \left(\hat{\beta}_{FEM} - \hat{\beta}_{REM}\right)'[var(\hat{\beta}_{FEM} - \hat{\beta}_{REM})]^{-1}\left(\hat{\beta}_{FEM} - \hat{\beta}_{REM}\right) \quad (6)$$

where $\hat{\beta}_{FEM}$ is vector of coefficients of independent variables from FEM and $\hat{\beta}_{REM}$ is vector of independent variable coefficients from REM.

Decision:

- If p-value ≤ α, then the initial hypothesis ($\mathrm{H_0}$) is rejected, which means that the selected model is FEM.
- If the p-value > α, then the initial hypothesis ($\mathrm{H_0}$) is not rejected, which means that the selected model is REM.

3) Lagrange Multiplier (LM) Test

The LM test is used to choose a better model between CEM and REM by carrying out REM testing based on the residual value of CEM.

Hypothesis:

$\mathrm{H_0}$: Common Effect Model (CEM)

$\mathrm{H_1}$: Random Effect Model (REM)

The statistical value of the LM test can be calculated using the formula in equation (7).

$$LM = \frac{NT}{2(T-1)}\left[\frac{\sum_{i=1}^{T}[\sum_{t=1}^{T}\varepsilon_{it}]^2}{\sum_{i=1}^{K}\sum_{t=1}^{T}\varepsilon_{it}^2} - 1\right]^2 \tag{7}$$

where N is number of individuals, T is many periods, and ε_{it} is combined model residual.

Decision:

- If p-value ≤ α, then the initial hypothesis ($\mathrm{H_0}$) is rejected, which means that the selected model is REM.
- If the p-value > α, then the initial hypothesis ($\mathrm{H_0}$) is not rejected, which means that the selected model is CEM.

d. The Assumptions of the Panel Data Regression Model

1) Normality Test

Wooldridge (2016) demonstrated that assume normality is not needed for large panel data, which includes both time and different groups. The Central Limit Theorem (CLT) guarantees that the estimator's distribution will become normal even if the errors aren't. Greene (2018) also highlights that for OLS models and panel data, normality is not required as long as the sample size is large. For models that use maximum likelihood, like logit or probit models, it's more important for the data to be normal, but for models that use least squares, like OLS and panel models, the Central Limit Theorem will help with the error distribution when the sample size is large.

2) Multicollinearity Test

The multicollinearity test was carried out to assess whether there is a correlation between the independent variables in this regression model. This method is used to identify multicollinearity problems by evaluating simple correlation values between independent variables. This assumption requires the variable to have a Variance

Inflation Factors (VIF) value smaller than 10. If the VIF value is greater than 10, it can be concluded that the research model experiences a multicollinearity problem(Greene, 2018).

3) Heteroscedasticity Test

This test aims to test whether there is a difference in the residual variance between one observation (Peng et al., 2021). Heteroskedasticity can be seen using the white method. The white test aims to identify whether the residual variance is not constant (Feng et al., 2020). The method commonly used in the white test is to regress the squared residuals against all explanatory variables in the model (Han & Kim, 2023; Wang et al., 2024).

Decision:

- If the p-value $< \alpha$, there is a heteroscedasticity
- If the p-value $\geq \alpha$, there is no a heteroscedasticity.

4) Autocorrelation Test

Autocorrelation arises when the residuals at one temporal point are correlated with the residuals at another temporal moment within the same individual unit (Kumar, 2023). In the realm of panel data, this indicates that errors at one temporal juncture can influence errors at the subsequent temporal juncture for the same entity. The consequences of correlation include inaccurate estimation, erroneous standard error, and misinterpretation. The Wooldridge Test for autocorrelation is frequently employed to identify autocorrelation in panel data (Born & Breitung, 2016; Chen, 2022). The remedy for autocorrelation is to employ clustered standard errors for each individual unit.

Decision:

- If the p-value $< \alpha$, there is an autocorrelation.
- If the p-value $\geq \alpha$, there is no an autocorrelation

e. Parameter Testing

1) Partial Test (t-Test)

The partial test tests whether the independent variable (individually) affects the dependent variable (Wooldridge, 2016). The t-test statistical formula used can be seen in equation (8).

$$t = \frac{r_{xy}\sqrt{(N-2)}}{\sqrt{(1-r_{xy}^2)}} \tag{8}$$

where r_{xy} is partial correlation coefficient of independent variables to dependent variable. The hypothesis used in the t-test is:

H_0: $\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$, the independent variable partially has no significant effect on the dependent variable in the model.

H_1: $\beta_1 \neq \beta_2 \neq \beta_3 \neq \beta_4 \neq \beta_5 \neq 0$, the independent variable partially has a significant effect on the dependent variable in the model.

Decision:
- If the p-value ≤ α, then H_0 is rejected, which means that the independent variable partially has a significant effect on the dependent variable in the model.
- If the p-value > α, then H_0 is not rejected, which means that the independent variable partially has no significant effect on the dependent variable in the model.

2) Simultaneous Test (F-Test)

The simultaneous test or F-test is carried out to determine the effect of the independent variables on the dependent variable (Greene, 2018). With test statistics written in equation (9).

$$F = \frac{R^2/(N+K-1)}{(1-R^2)/(NT-N-K)} \tag{9}$$

where R^2 is correlation coefficient squared, K is number of independent variables including constants, and N is number of samples. The hypothesis used in the F-test is:

H_0: $\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$, the independent variables simultaneously have no significant effect on the dependent variable

H_1: $\beta_1 \neq \beta_2 \neq \beta_3 \neq \beta_4 \neq \beta_5 \neq 0$, the independent variables simultaneously have a significant effect on the dependent variable

Decision:
- If the p-value ≤ α, then H_0 is rejected, which means that the independent variable simultaneously significantly affects the dependent variable in the model.
- If the p-value > α, then H_0 is not rejected, which means that the independent variables simultaneously do not significantly affect the dependent variable in the model.

3) Coefficient of Determination

The coefficient of determination measures how much the independent variable can explain the dependent variable (Greene, 2018). Suppose the coefficient of determination value is close to 1. In that case, the influence of the independent variable on the dependent variable is strong. If the coefficient of determination value is 0, then the independent variable does not impact the dependent variable. The test statistics are written in equation (10).

$$KD = R^2 \times 100\% \tag{10}$$

where KD is coefficient of determination.

f. Model Specifications

The model in this research can be seen in equation (11).

$$\mathrm{H}DI_{\mathrm{it}} = \beta_0 + \beta_1 \mathrm{LEB}_{it} + \beta_2 \mathrm{EYS}_{it} + \beta_3 \mathrm{MYS}_{it} + \beta_4 \mathrm{APE}_{\mathrm{it}} + \beta_5\ \mathrm{NPP}_{\mathrm{it}} + \varepsilon_{\mathrm{it}} \quad (11)$$

where t is the t-th period with t =2010, 2011, ..., 2023 and i is the i-th observations unit with i= Lombok Barat, Lombok Timur, Lombok Tengah, ..., Mataram.

g. Standardized Coefficient

The beta or standardized coefficients is typically performed to determine which independent variables exert a bigger influence on the dependent variable in a multiple regression analysis involving variables measured in disparate units. It can also be regarded as a universal metric of effect size, assessing the "magnitude" of the influence of one variable on another. The standardized coefficients can be determined by applying the formula in equation (12) to a simple linear regression or multivariable linear or panel regression model that has been estimated to report the regression coefficient between the respon and predictor variable (Nieminen, 2022; Sachs et al., 2025; van Ginkel, 2020).

$$\widehat{\boldsymbol{\beta}}^* = \begin{bmatrix} \beta_1 \dfrac{SD_{x1}}{SD_y} \\ \vdots \\ \beta_K \dfrac{SD_{xK}}{SD_y} \end{bmatrix} \quad (12)$$

where $\widehat{\boldsymbol{\beta}}^*$ is vector of standardized coefficients, SD_x is the standard deviation of predictor variable, and SD_y is the standard deviation of respon variable.

h. Analysis Stages

The data analysis process in this research uses R software. The flowchart for conducting panel data regression analysis is presented in Figure 1. Details of the stages of panel data regression analysis based on the data analysis flow are presented as follows:

1) Preparing the data, ensuring that the data to be used has been collected and is available in panel data format. The data used in the analysis process has been natural logarithmized to allow coefficients to be interpreted as elasticities .
2) Identifying and defining dependent variables and independent variables.
3) Exploring the data, namely, finding out the pattern of relationships between variables through scatterplots and analyzing them descriptively.
4) Choosing a regression model, namely, determining the type of regression model that suits the research problem. Panel data regression models can include CEM, FEM, or REM.
5) Carrying out the classic assumption tests, namely: the assumptions of multicollinearity, autocorrelation, and heteroscedasticity.
6) Estimating the parameters: using the panel data regression method to obtain the coefficients of each variable used to model the HDI.
7) Computing the standardized coefficients based on coefficients regression in step(6)

8) Interpreting the results.

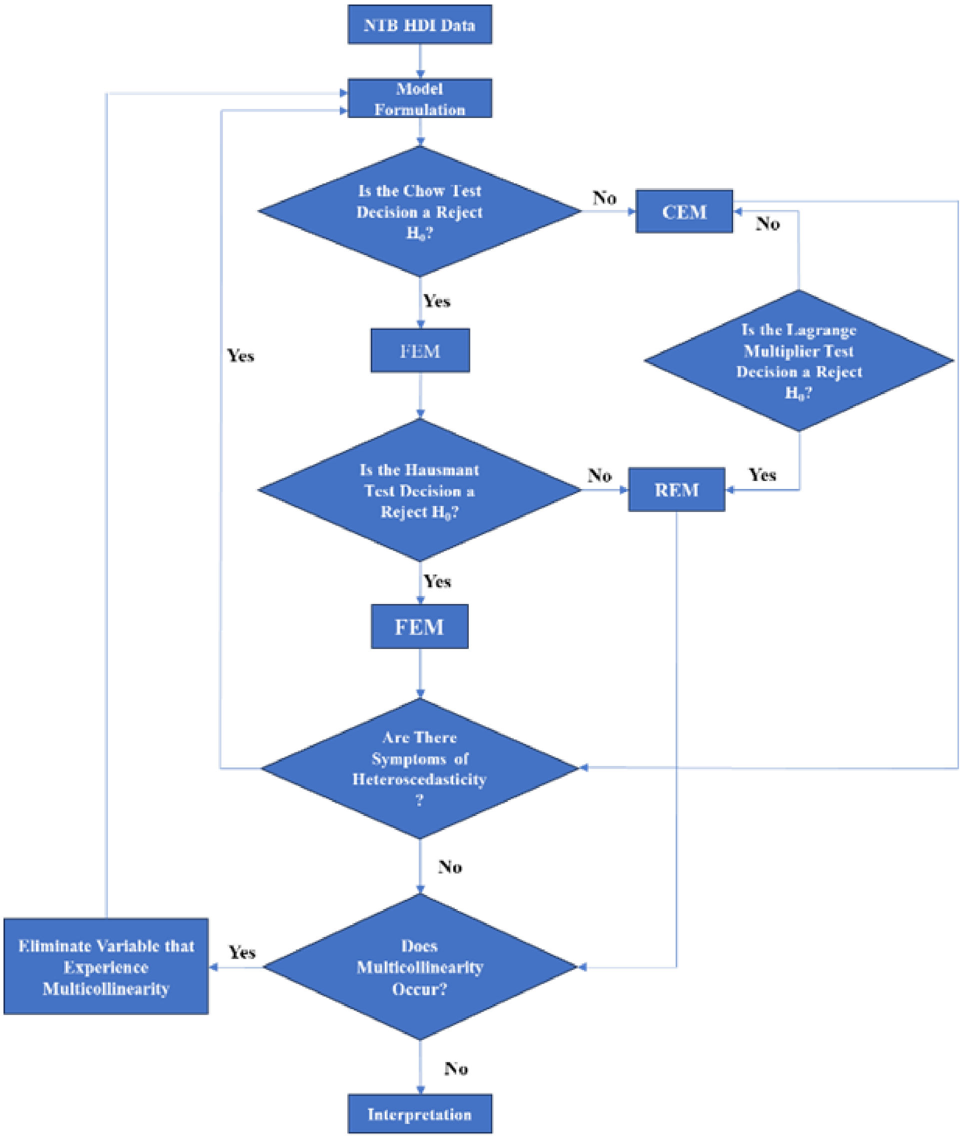


Figure 1. Analysis Flowchart

C. RESULT AND DISCUSSION

1. Descriptive Statistical Analysis

The results of descriptive statistical analysis of research data are presented in Table 2.

Table 2. Descriptive Statistics of Research Variables

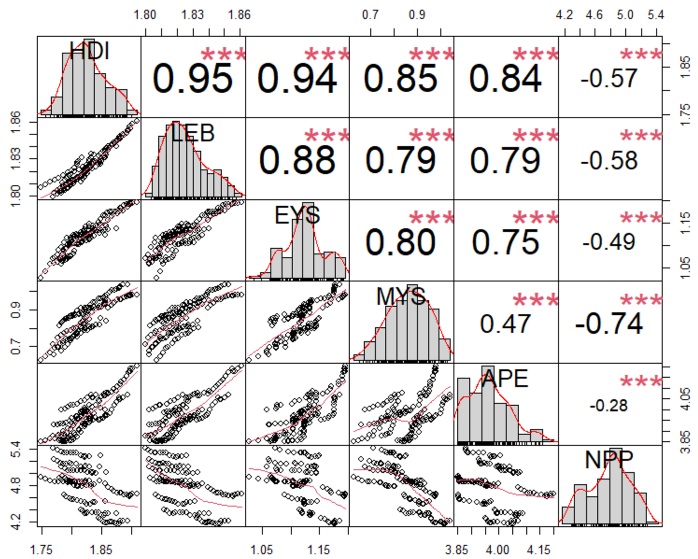
Variable	Statistic				
	Mean	Median	Max.	Min.	Std. Dev.
HDI	66.74	66.26	79.59	56.13	5.34
LEB	66.52	66.13	72.20	63.03	2.18
EYS	13.28	13.25	15.65	10.66	1.11
MYS	7.28	7.23	10.94	4.23	1.55
APE	9,555,000	9,185,000	15,426,000	7,083,000	1,964,000
NPP	80,287	71,170	263,690	14,660	58,958

The districts/cities human development index in NTB province from 2010 to 2023 has an average value of 66.74%. The highest human development index reached 79.59%, while the minimum value reached 56.13%. Meanwhile, the average of life expectancy at birth in NTB province during the same period was 66.52 years. The highest life expectancy at birth reached 72.20 years, while the lowest was 63.03. The expected years of schooling in NTB province shows an average of 13.28 years, with a maximum value of 15.56 years and a minimum of 10.66 years.

Analysis of the mean years of schooling in NTB province from 2010 to 2023 found the highest point was 10.94 years, while the lowest point was only 4.23 years, with an average value of 7.28 years. NTB province's per capita expenditure shows an average of 9,555,000 IDR. The maximum value reaches 15,426,000 IDR, while the minimum value reaches 7,083,000 IDR Meanwhile, the number of poor people in NTB province from 2010 to 2023 shows an average of 80,286 people, with the highest peak reaching 263,690 people and the lowest point reaching 14,660 people.

2. Correlation of The Research Variables

The relationship between the human development index, life expectancy at birth, expected years of schooling, mean years of schooling, adjusted per capita expenditure, and the number of poor people is presented in Figure 2. The positive relationship in Figure 2 is marked by a linear line that goes to the right, increasing. Meanwhile, a negative relationship is indicated by a linear line that decreases further to the right at lower triangle of Figure 2. In addition, the correlation values between variables are presented in upper triangle of Figure 2.



Notes: *** Significant at α = 5%.

Figure 2. Scatterplot Matrix of Research Variables Correlation

Life expectancy at birth, expected years of schooling, mean years of schooling, and adjusted per capita expenditure exhibit a significant positive correlation with the human development index. The number of poor people adversely and significantly affects the human development index. Districts/cities exhibiting higher life expectancy characteristics can enhance the human development index in the NTB province, or conversely. The expected years of schooling are positively correlated with the human development index in the province of NTB. The mean years of schooling and adjusted per capita expenditure are comparable. An increased mean years of schooling can enhance the human development index. Areas exhibiting elevated adjusted per capita expenditure have the potential to enhance the human development index. The number of poor people exhibits a negative and significant correlation with the human development index. An increase in the number of poor people within a district or city correlates with a decline in the development index.

3. Inferential Statistical Analysis

a. Panel Model Estimation

This research uses panel data using three regression models, namely the Common Effect Model (CEM), Fixed Effect Model (FEM), and Random Effect Model (REM). The estimation results of the three models are presented in Table 3.

Table 3. Panel Data Model Estimation Result

Variable	CEM		FEM		REM	
	Coefficient	**p-value**	**Coefficient**	**p-value**	**Coefficient**	**p-value**
Constant	0.100	0.130			-0.140	0.051
LEB	0.555	0.000	0.849	0.000	0.577	0.000
EYS	0.193	0.000	0.196	0.000	0.189	0.000
MYS	0.129	0.000	0.113	0.000	0.131	0.000
APE	0.146	0.000	0.153	0.000	0.146	0.000
NPP	0.002	0.178	0.035	0.000	0.002	0.104

The results in Table 3 indicate that life expectancy at birth (LEB), expected years of schooling (EYS), mean years of schooling (MYS), adjusted per capita expenditure (APE), and number of poor people (NPP) significantly affect HDI in the Fixed Effect Model. However, in the Common Effect and Random Effect Models, the number of poor people has no significant impact on the human development index.

b. Panel Model Selection

Three tests were carried out to determine the best regression model in panel data analysis, namely the Chow test, Hausman test, and Lagrange Multiplier test. The results of the panel model selection are described below.

1) Chow Test

The Chow test results are presented in Table 4, which informs that the p-value of Cross-Section F is 0.000. This value is smaller than the significance level (α) for α = 5%. This means that H_0 is rejected. Therefore, the model chosen is the Fixed Effect Model.

Table 4. Chow Test Results

Effect Test	Statistic	Degree of freedom	p-value	Decision
Cross-section F	8.059	(9;125)	0.000	H_0 is rejected

2) Hausman Test

The Hausman test results are presented in Table 5, which informs the p-value of the Cross-Section Random is 0.000. This value is less than significance level (α) for α = 5%. This means that H_0 is rejected. Thus, the Fixed Effect Model is chosen model. As a result, the analytical process did not advance to the Lagrange multiplier test.

Table 5. Hausman Test Results

Test Summary	Chi-Sq. Statistic	Degree of freedom	p-value	Decision
Cross-section Random	87.415	5	0.000	H_0 is rejected

The panel model selection results show that the best panel model for modeling the human development index in the NTB province for 2010-2023 is the fixed effect model, which can be seen in equation (13).

$$\widehat{\mathrm{HDI}}_{\mathrm{it}} = \beta_0 + \mu_i + 0.849\mathrm{LEB}_{\mathrm{it}} + 0.196\mathrm{EYS}_{\mathrm{it}} + 0.113\mathrm{MYS}_{\mathrm{it}} + 0.153\mathrm{APE}_{\mathrm{it}} + 0.035\mathrm{NPP}_{\mathrm{it}} \tag{13}$$

where value of $\beta_0 + \mu_i$ can be seen in Table 6.

Table 6. Effect of Districts/Cities

i	Districts/Cities	Value
1	Lombok Barat	-0.827
2	Lombok Tengah	-0.830
3	Lombok Timur	-0.835
4	Sumbawa	-0.821
5	Dompu	0.808
6	Bima	-0.819
7	Sumbawa Barat	-0.803
8	Lombok Utara	-0.822
9	Mataram	-0.826
10	Bima City	-0.802

c. Classic Assumption Test

1) Multicollinearity Test

The results of the multicollinearity test of the regression model are presented in Table 7. Based on Table 7, no variables have a VIF value is more than 10, meaning that all independent variables in this study do not experience multicollinearity problems.

Table 7. Multicollinearity Test Results

Variable	VIF
LEB	9.448
EYS	7.946
MYS	6.416
APE	4.125
NPP	2.323

2) Heteroscedasticity and Autocorrelation Test

The result of heteroscedasticity and autocorrelation test is presented in Table 8. The value of Breusch-Pagan test for heteroskedasticity is 13.700 with p-value is 0.017. This indicates that the assumption of homoscedasticity is violated. For autocorrelation, the value of Wooldridge test is 96.415 with p-value is 0.000. This signifies a breach of the autocorrelation assumption. The existence of heteroskedasticity and autocorrelation issues in the regression model still yields unbiased and consistent parameter estimations. Nevertheless, the parameter estimator exhibits suboptimal variance. This will influence the hypothesis test's conclusion, resulting in erroneous outcomes as it fails to represent the true circumstances.

Table 8. Heteroscedasticity and Autocorrelation Test Result

Test	Statistics	df	p-value	Decision
Breusch-Pagan (Heteroskedasticity)	13.700	5	0.017	There is heteroscedasticity
Wooldridge (Autocorrelation)	96.415	14	0.000	There is an autocorrelation

Atkinson et al. (2016) and Pötscher & Preinerstorfer (2025) provide a robust approach utilizing a parameterized variance function to resolve the the heteroskedasticity and autocorrelation issue, namely Newey-West test. The Newey-West test is employed to adjust the standard error of parameter estimators, enhancing their robustness against both heteroskedasticity and autocorrelation. The result of Newey West test is presented in Table 9.

Table 9. Heteroscedasticity and Autocorrelation Test Result

Variable	Estimation	FEM		Newey-West	
		Standard Error	p-value	Standard Error	p-value
LEB	0.849	0.1250	3.81E-10	0.0852	2.20E-16
EYS	0.196	0.0243	6.01E-13	0.0306	3.00E-09
MYS	0.113	0.0208	3.01E-07	0.0214	5.95E-07
APE	0.153	0.0155	2.20E-16	0.0146	2.20E-16
NPP	0.035	0.0101	6.46E-04	0.0078	1.36E-05

Table 9 reveals that the estimated parameters obtained are consistent. This parameter estimator is both unbiased and consistent. The distinction between the two models is in the standard error of the parameter estimates, which will influence the significance of hypothesis testing (p-value).

d. Parameter Significance Test

Parameter significance test carried out in this research consisted of partial test (t-test), simultaneous test (F-test), and coefficient of determination tests (R^2). The results of these three tests are as follows.

1) Partial Test (t-Test)

   The t-test results for the Fixed Effect Model are presented in Table 3 and Table 9, informs that life expectancy at birth, expected years of schooling, mean years of schooling, and adjusted per capita expenditure exhibit a significant positive effect with the human development index in NTB Province.

2) Simultaneous Test (F-Test)

   The results of the F-test using the Random Effect Model are presented in Table 10. The test results using the Fixed Effect Model reveals that the p-value of F-test is 0.000, where this value is less than the significance level for α = 0.05. This means that H_0 is rejected. Thus, it can be concluded that life expectancy at birth, expected years of schooling, mean years of schooling, adjusted per capita expenditure, and the number of poor people simultaneously significantly affect the human development index in NTB province.

Table 10. F-Test Results

Statistics	Value
R-squared	0.9871
Adjusted R-squared	0.9856
F-statistic	1,905.370
Degree of freedom	(5;125)
p-value	0.000

3) Coefficient of Determination Test

   Table 10 shows that the R-squared value is 0.9871, which indicates that the model explains 98.71% of the variance in the HDI by life expectancy at birth, expected years of schooling, mean years of schooling, adjusted per capita expenditure, and the number of poor people in the powerful category. Meanwhile, the remaining 1.29% is explained by other variables not used in this research. To identify the most contributing independent variable, it is essential to compute the standardized regression coefficient, as presented in Table 11.

Table 11. The Standardized Coefficient of The Independent Variables

Variable	Standardized Coefficient
LEB	0.349
EYS	0.202
MYS	0.304
APE	0.374
NPP	0.342

Table 11 proves that adjusted per capita expenditure is the most greatly impacts human development index in West Nusa Tenggara in 2010-2023. Life expectancy index at birth, number of poor people, and mean years of schooling occupy the second, third, and fourth positions, respectively, as determinants that substantially affect human development index in NTB. The expected years of schooling is the variable that contributes the least to the entire components of the HDI in NTB.

This study's findings align with the research of Setiawan (2023). Adjusted per capita expenditure indicates an individual's ability to fulfill essential requirements. An increase in adjusted per capita expenditure correlates positively with the likelihood of individuals accessing healthcare, education, and essential living necessities, thereby enhancing the Human Development Index. Adjusted per capita expenditure is a significant factor in the improvement of HDI. Allocating expenditure towards productive sectors, such as education and health, positively influences human development. The findings of this study regarding life expectancy are consistent with the research by Faiza & Hayati (2024) and Singh et al. (2025), indicating that an increase in life expectancy significantly enhances the Human Development Index (HDI). Life expectancy serves as a crucial metric within the health component of the Human Development Index. Increased life expectancy correlates with improved public health quality, indicating the efficacy of the healthcare system and the overall welfare level. These factors may enhance the human development index indirectly.

In contrast to the variable concerning the number of poor people. This study's results indicate a positive and significant effect on the Human Development Index in NTB. Theoretically, the prevalence of poverty (number of poor people) negatively affects the Human Development Index, as poverty correlates with restricted access to education, health, and essential expenditures, which constitute the three primary dimensions of the human development index. The research by Awary and Nilasari (2025) indicates that the population of impoverished individuals adversely affects the human development index in a significant manner. The positive and significant influence of the number of impoverished individuals on the human development index does not suggest that poverty is beneficial; instead, it indicates the effectiveness of development interventions that have successfully targeted the poor population, particularly in education and health sectors. This study demonstrates the significance of policy bias and the effectiveness of social spending in advancing human development, despite the challenges posed by poverty.

Education serves as a fundamental pillar in the development of human capacity. The mean years of schooling indicates the current level of education attained, whereas the expected years of schooling signifies the potential educational attainment for today's children. Sasmita et al. (2023) assert that the increase in RLS and HLS is closely associated with the rise in HDI, as it enhances the economic and social capabilities of individuals. The findings indicate that sustainable human development is not dependent on a singular variable; rather, it results from the interplay of multiple factors. Consequently, effective development policies should address and enhance all these variables to attain sustainable social and economic advancement in West Nusa Tenggara Province.

D. CONCLUSION AND SUGGESTIONS

The adjusted per capita expenditure had the greatest impact on the human development index of NTB Province in 2010–2023. The expected years of schooling was the variable that contributed the least to the entire components of the HDI in NTB province. The number of poor people had a significant effect on the human development index of NTB province from 2010 to 2023. The influence given was positive. For the government: the government ought to prioritize enhancing the quality and sustainability of long-term education. A significant number of children in NTB province discontinue their education following the completion of basic schooling. The government must enhance the accessibility of secondary schools and higher education institutions, particularly in rural regions and isolated islands. Furthermore, establish educational pathways that correspond with the demands of the local employment market to enhance public engagement in advanced education. For future researchers: consider incorporating other variables such as the unemployment rate, income inequality, female labor force participation, or local government expenditure in education and health sectors to discern additional factors that may affect the HDI. The scatterplot indicates a non-linear relationship between the number of poor people and HDI. Consequently, employing non-linear regression to analyze the determinants influencing the HDI in NTB is recommended.

ACKNOWLEDGEMENT

The authors would like to thank the editors and reviewers for their insightful comments and constructive criticism, which helped improve this article.

REFERENCES

Anekawati, A., Purhadi, Rofik, M., & Hidayat, S. (2024). A Spatial Error Model in Structural Equation for the Human Development Index Modeling. *International Journal of Mathematical, Engineering and Management Sciences*, *9*(3), 537–556. https://doi.org/10.33889/IJMEMS.2024.9.3.028

Astuti, A. M., Afifurrahman, & Negara, H. R. P. (2024). Analysis of Human Development Index in West Nusa Tenggara Province with Spatial Panel Model. *International Journal of Computing Science and Applied Mathematics*, *10*(2), 113–118. https://doi.org/10.12962/j24775401.v10i2.21957

Astuti, A. M., Ashri, E. S., & Sabri, S. (2024). Modeling Life Expectancy Index in West Nusa Tenggara Province with Panel Regression Method. *Inferensi*, *7*(1), 53. https://doi.org/10.12962/j27213862.v7i1.20148

Astuti, A. M., Setiawan, S., Zain, I., & Purnomo, J. D. T. (2020). A Review of Panel Data on Spatial Econometrics Models. *Journal of Physics: Conference Series*, *1490*(1), 1–13. https://doi.org/10.1088/1742-6596/1490/1/012032

Astuti, A. M., Setiawan, S., Zain, I., & Purnomo, J. D. T. (2021). The extended algorithm for quasi maximum likelihood parameter estimation. *AIP Conference Proceedings*, *2360*, 1–5. https://doi.org/10.1063/5.0059509

Astuti, A. M., Setiawan, S., Zain, I., & Purnomo, J. D. T. (2023). A modified generalized estimating equation approach for simultaneous spatial durbin panel model: Case study of economic growth in ASEAN countries. *Decision Science Letters*, *12*(2), 369–388. https://doi.org/10.5267/dsl.2023.1.001

Atkinson, A. C., Riani, M., & Torti, F. (2016). Robust methods for heteroskedastic regression. *Computational Statistics & Data Analysis*, *104*, 209–222. https://doi.org/10.1016/j.csda.2016.07.002

Awary, N., & Nilasari, A. (2025). The Influence of Poverty, Unemployment, and Economic Growth on the Human Development Index (HDI) in East Java Province 2020-2023. *Formosa Journal of Multidisciplinary Research*, *4*(4), 1615–1630. https://doi.org/10.55927/fjmr.v4i4.144

Baltagi, B. H. (2021). *Econometrics* (Sixth). Springer.

Belotti, F., Hughes, G., & Mortari, A. P. (2017). Spatial panel-data models using Stata. *Stata Journal*, *17*(1), 139–180. https://doi.org/10.1177/1536867x1701700109

Born, B., & Breitung, J. (2016). Testing for Serial Correlation in Fixed-Effects Panel Data Models. *Econometric Reviews*, *35*(7), 1290–1316. https://doi.org/10.1080/07474938.2014.976524

BPS-Statistics Indonesia. (2024). *Indeks Pembangunan Manusia 2023* (Direktorat Analisis dan Pengembangan Statistik, Ed.; Vol. 18). Badan Pusat Statistik Republik Indonesia.

BPS-Statistics Indonesia. (2025). *Human Development Index 2024* (Vol. 19). Badan Pusat Statistik.

BPS-Statistics NTB Province. (2023). *Nusa Tenggara Barat Province in Figures 2022*. BPS Provinsi Nusa Tenggara Barat.

Chen, B. (2022). A robust test for serial correlation in panel data models. *Econometric Reviews*, *41*(9), 1095–1112. https://doi.org/10.1080/07474938.2022.2091362

Dewi, A. K., & Nurhayati, S. F. (2023). Analysis Effect of Human Development Index (HDI), Regency/City Minimum Wage (UMK), Investment and Unemployment Rate on the Number of Poor People in Bali Province in 2012-2021. *Wiga : Jurnal Penelitian Ilmu Ekonomi*, *13*(1), 95–102. https://doi.org/10.30741/wiga.v13i1.933

Faiza, U. N., & Hayati, M. (2024). Factors Influencing the Human Development Index (HDI) in Lampung Province: A Multiple Linear Regression Analysis. *Symmetry & Sigma: Journal of Mathematical Structures and Statistical Patterns*, *1*(2), 148–164. https://doi.org/10.58989/symmerge.v1i2.27

Feng, S., Li, G., Tong, T., & Luo, S. (2020). Testing for heteroskedasticity in two-way fixed effects panel data models. *Journal of Applied Statistics*, *47*(1), 91–116. https://doi.org/10.1080/02664763.2019.1634682

Gallo, L. J., & Pirotte, A. (2017). Models for Spatial Panels. In L. Matyas (Ed.), *The Econometrics of Multi-dimensional Panels. Theory and Applications* (pp. 263–289). Springer International Publishing. https://mdpd2ed.ceu.edu/CompiledBook.pdf

Greene, W. H. (2018). *Econometric Analysis* (Eighth). Pearson.

Han, C., & Kim, H. (2023). Heteroskedasticity-Robust Standard Errors for Dynamic Panel Data Models with Fixed Effects*. *Oxford Bulletin of Economics and Statistics*, *85*(5), 1135–1155. https://doi.org/10.1111/obes.12554

Herre, B., & Arriagada, P. (2023, November 1). *The Human Development Index and related indices: what they are and what we can learn from them*. OurWorldinData.Org. https://ourworldindata.org/human-development-index

Humaira, U. H., & Nugraha, J. (2018). Analysis of Factors Affecting the Human Development Index in West Kalimantan Province using Data Panel Data Regression. *Eksakta: Jurnal Ilmu-Ilmu MIPA*, *18*(2), 97–105. https://doi.org/10.20885/eksakta.vol18.iss2.art2

Jalil, S. A., & Kamaruddin, M. N. (2018). Examining the Relationship between Human Development Index and Socio-Economic Variables: A Panel Data Analysis. *Journal of International Business, Economics and Entrepreneurship*, *3*(2), 37–44. https://doi.org/10.24191/jibe.v3i2.14431

Kamil, M. A. Z., Kurniawan, A., & Amelia, D. (2024). Modeling of Human Development Index (HDI) in Indonesia Using Multivariate Adaptive Regression Spline Method. *International Journal of Academic and Applied Research*, *8*(6), 72–80. http://ijeais.org/wp-content/uploads/2024/6/IJAAR240610.pdf

Kumar, N. K. (2023). Autocorrelation and Heteroscedasticity in Regression Analysis. *Journal of Business and Social Sciences*, *5*(1), 9–20. https://doi.org/10.3126/jbss.v5i1.72442

Lee, L.-F., & Yu, J. (2015). Identification of Spatial Durbin Panel Models. *Journal of Applied Econometrics*, *30*(1), 133–162. https://doi.org/10.1002/jae.2450

Lind, N. (2019). A Development of the Human Development Index. *Social Indicators Research*, *146*(3), 409–423. https://doi.org/10.1007/s11205-019-02133-9

Mangaraj, B. K., & Aparajita, U. (2020). Constructing a generalized model of the human development index. *Socio-Economic Planning Sciences*, *70*, 100778. https://doi.org/10.1016/j.seps.2019.100778

Nieminen, P. (2022). Application of Standardized Regression Coefficient in Meta-Analysis. In *BioMedInformatics* (Vol. 2, Issue 3, pp. 434–458). Multidisciplinary Digital Publishing Institute (MDPI). https://doi.org/10.3390/biomedinformatics2030028

Nur, B., & Yuliansyah, R. (2020). The Influence of Revenues and Capital Expenditures to the Human Development Index at 4 Provinces in Indonesia. *Proceedings of the Annual International Conference on Accounting Research (AICAR 2019)*, 69–72. https://doi.org/10.2991/aebmr.k.200309.016

Peng, B., Yu, J., & Zhu, Y. (2021). A heteroskedasticity robust test for cross-sectional correlation in a fixed effects panel data model. *Economics Letters*, *201*, 109799. https://doi.org/10.1016/j.econlet.2021.109799

Pertiwi, Y., Permana, D., Amalita, N., & Salma, A. (2023). Modeling Human Development Index in Papua and West Sumatera with Multivariate Adaptive Regression Spline. *UNP Journal of Statistics and Data Science*, *1*(3), 188–195. https://doi.org/10.24036/ujsds/vol1-iss3/54

Pötscher, B. M., & Preinerstorfer, D. (2025). Valid Heteroskedasticity Robust Testing. *Econometric Theory*, *41*(2), 249–301. https://doi.org/10.1017/S0266466623000269

Pramesti, W., & Indrasetianingsih, A. (2018). East Java Human Development Index Modeling with Spatial Regression Approach. *Proceedings of the 1st International Conference on Social Sciences (ICSS 2018)*, 1494–1498. https://doi.org/10.2991/icss-18.2018.312

Pramesti, W., & Suharsono, A. (2019). Spatial autoregressive model for modeling of human development index in East Java province. *International Journal of Mechanical Engineering and Technology*, *10*(1), 626–632. https://paper.researchbib.com/view/paper/211799

Pramuja, R. A., Sari, N. P., Arifin, Z., Azizurrohman, M., & Supiandi, S. (2023). Long- and short-term analysis on the Human Development Index in West Nusa Tenggara. *Journal of Enterprise and Development*, *5*(1), 58–72. https://doi.org/10.20414/jed.v5i1.6764

Purba, B. (2019). Analysis of Human Development Index in The Highlands Region of North Sumatera Province Indonesia. *The 1st Multi-Disciplinary International Conference*. https://www.semanticscholar.org/paper/ANALYSIS-OF-HUMAN-DEVELOPMENT-INDEX-IN-THE-REGION-Purba/bc5c3e805afc5c80ce01a1170ffafbd9ce35563e#citing-papers

Rahmawati, D. P., Budiantara, I. N., Prastyo, D. D., & Octavanny, M. A. D. (2021). Modeling of Human Development Index in Papua Province Using Spline Smoothing Estimator in Nonparametric Regression. *Journal of Physics: Conference Series*, *1752*(1). https://doi.org/10.1088/1742-6596/1752/1/012018

Rayes, F. A. P. (2019). *Human Development Analysis: The Role of Demographic Factors in West Nusa Tenggara in The Period of 2013-2017* [Scientific Journal, Universitas Brawijaya]. https://repository.ub.ac.id/id/eprint/174627/

Sachs, M. C., Ohlendorff, J. S., Brand, A., Sjölander, A., & Gabriel, E. E. (2025). The next generation of regression standardization with the R package stdReg2. *Annals of Epidemiology*, *105*, 66–74. https://doi.org/10.1016/j.annepidem.2025.04.002

Sapurah, S., Gunartha, I. G. E., & Fitriyani, N. (2021). Panel Data Regression Analysis of Human Development Index in West Nusa Tenggara Province with Fixed Effect Model. *Eigen Mathematics Journal*, *4*(2), 60–67. https://doi.org/10.29303/emj.v4i2.114

Saputro, D. R. S., Hastutik, R. D., & Widyaningsih, P. (2021). The modeling of human development index (HDI) in Papua-Indonesia using geographically weighted ridge regression (GWRR). *AIP Conference Proceedings*, 020025. https://doi.org/10.1063/5.0040329

Sari, P. B. K. (2022). Determinants of Human Development Index in East Java Province. *Efficient: Indonesian Journal of Development Economics*, *5*(1), 1494–1504. https://doi.org/10.15294/efficient.v5i1.50286

Sasmita, N. R., Phonna, R. A., Fikri, M. K., Khairul, M., Apriliansyah, F., Idroes, G. M., Puspitasari, A., & Saputra, F. E. (2023). Statistical Assessment of Human Development Index Variations and Their Correlates: A Case Study of Aceh Province, Indonesia. *Grimsa Journal of Business and Economics Studies*, *1*(1), 12–24. https://doi.org/10.61975/gjbes.v1i1.14

Setiawan, A. (2023). Relationship model among human development index, Gini coefficient, per capita non-food expenditure, per capita gross regional domestic product and development financing in provinces in Indonesia for the 2015-2019 period. *AIP Conference Prosiding*, 030008. https://doi.org/10.1063/5.0177428

Singh, K., Cheemalapati, S., RamiReddy, S. R., Kurian, G., Muzumdar, P., & Muley, A. (2025). Determinants of Human Development Index (HDI): A Regression Analysis of Economic and Social Indicators.

Asian Journal of Economics, Business and Accounting, *25*(1), 26–34. https://doi.org/10.9734/ajeba/2025/v25i11630

Susanti, Y., Nirwana, M. B., & Prichanti, L. A. (2025). Modelling of human development index (HDI) in Indonesia using generalize scale (GS) estimation robust regression. *AIP Conference Prociding*, 020033. https://doi.org/10.1063/5.0262926

Tobaigy, F., Alamoudi, M., & Bafail, O. (2023). Human Development Index: Determining and Ranking the Significant Factors. *International Journal of Engineering Research & Technology (IJERT)*, *12*(3), 231–245. https://doi.org/10.17577/IJERTV12IS030142

UNDP. (2022). *Human Development Report 2021/2022: Uncertain Times, Unsettled Lives Shaping Our Future in A Transforming World*. United Nations Development Programme. https://hdr.undp.org/content/human-development-report-2021-22

van Ginkel, J. R. (2020). Standardized Regression Coefficients and Newly Proposed Estimators for R2 in Multiply Imputed Data. *Psychometrika*, *85*(1), 185–205. https://doi.org/10.1007/s11336-020-09696-4

Wang, M., Kang, X., Liang, J., Wang, K., & Wu, Y. (2024). Heteroscedasticity identification and variable selection via multiple quantile regression. *Journal of Statistical Computation and Simulation*, *94*(2), 297–314. https://doi.org/10.1080/00949655.2023.2243533

Wathani, H. I., Asmony, T., & Herwanti, Rr. T. (2017). The Effect of Local Government Leader Characteristics and Audit Opinion on Local Government Performance and Its Implications on Human Development Index in West Nusa Tenggara. *Proceeding International Conference on Economics, Business and Information Technology (ICEBIT)*, 638–656. https://api.semanticscholar.org/CorpusID:211002684

Wooldridge, J. M. (2016). *Introductory Econometrics: A Modern Approach* (Sixth). Cengage Learning. www.cengage.com/highered

Yanuar, F., Tillah, M., & Devianto, D. D. (2018). Modeling of Human Development Index Using Ridge Regression Method. *EKSAKTA*, *19*(2), 1–11. https://doi.org/10.24036/eksakta/vol19-iss02/134

Yolanda, Y. (2017). Analysis of Factors Affecting Inflation and its Impact on Human Development Index and Poverty in Indonesia. *European Research Studies Journal*, *20*(4), 38–56. https://www.um.edu.mt/library/oar//handle/123456789/33040