Modeling Life Expectancy Index in West Nusa Tenggara Province with Panel Regression Method

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ABSTRACT – **Health is a condition of total physical, mental, and social well-being, rather than simply the lack of disease or weakness. One way to assess health indicators in a region is by enhancing the development of the health sector, which may be quantified using the life expectancy index (LEI). This study seeks to analyze the impact of average years of schooling, the adjusted per capita expenditure, and the number of poor people on life expectancy in NTB province from 2011 to 2020. The study's individual observation units consist of 10 regencies/cities in NTB Province. The data were obtained from BPS NTB in a panel data format and processed using the panel regression method. The panel model selection indicates that the Random Effect Model is the most suitable to predict the life expectancy in NTB province. The average years of schooling and the adjusted per capita expenditure have a notable impact on the life expectancy in NTB province. The effect provided is a beneficial impact. The number of poor people has a limited impact on life expectancy. Simultaneously, the average years of schooling, the adjusted per capita expenditure, and the number of poor people in the province of NTB have a substantial impact on the life expectancy.**

Keywords– **Regression Model, Panel Analysis, Life Expectancy**

I. INTRODUCTION

Health is a state of physical, mental, and social integrity, not just the absence of disease [1]. In addition, health is one of the Sustainable Development Goals (SDGs). It is because health is both an input and an outcome of development. Health is claimed to be the development input because a healthy body is the basic capital of an individual to work productively or to carry out other activities. It is also claimed as the development outcome because the progress of development allows the availability of decent health facilities for the community and facilitates the access of the community to better quality health services [2]. Measuring health indicators in a region is one way the local government attempts to enhance advancement in the health sector. The health status of a region can be assessed by the life expectancy index (LEI), which is strongly linked to the region's socio-economic progress. A high LEI in a region signifies advancing socio-economic development in that area. A low LEI signifies the decline of certain aspects of social and economic development in a region [3].

The annual report of the Badan Pusat Statistik (BPS) in West Nusa Tenggara (NTB) [2] indicates that the LEI of NTB province has risen in the past six years, as shown in Figure 1. An increase in the Life Expectancy Index (LEI) signifies an enhancement in public health conditions, allowing individuals the prospect of extended life expectancy due to improved health standards. The LEI of NTB province has grown annually but remains among the five lowest out of 34 provinces in Indonesia in 2022. Therefore, researchers are interested in studying the elements that influence the LEI in NTB province.

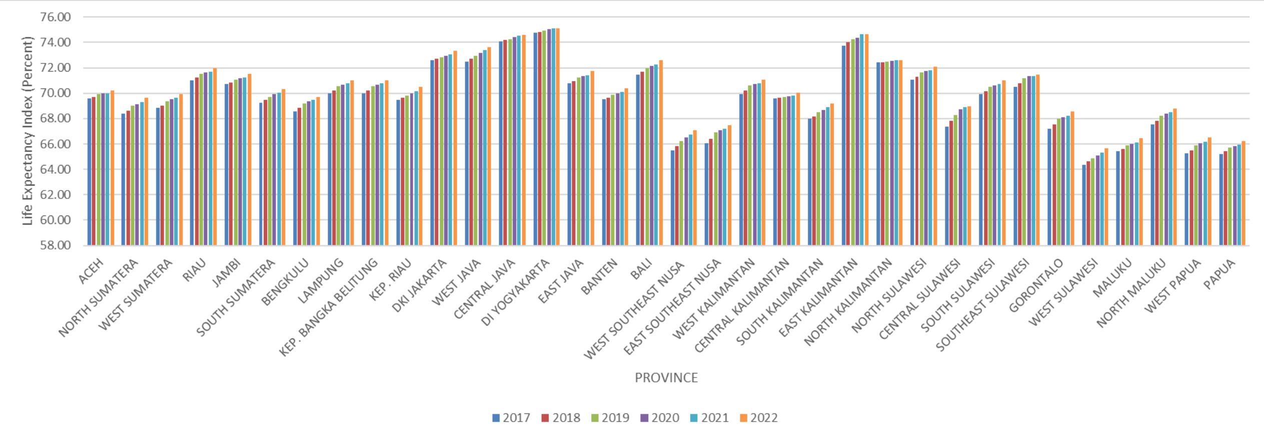

Figure 1. Life expectancy trends in Indonesia from 2017 to 2022

Research on LEI has been carried out by several scholars. Ramadhani et al. [4] conducted a study on the impact of various factors on LEI in Sumatera in 2018, including the proportion of malnourished youth, availability of nursing facilities in villages, access to sanitation, poverty rate, literacy rate among individuals aged 15 and above, and average years of schooling. They utilized spatial regression analysis for their research. Mukrom et al. [5] examined the effects of various factors on the socio-economic conditions in Central Java province in 2017 by utilizing the Robust Spatial Durbin Model. The factors included average school age, percentage of families practicing clean and healthy living, number of Posyandu facilities, percentage of the impoverished population, and per capita expenditure adjusted against LEI. Septianingsih [6] utilized variables such excellent drinking water sources, decent housing access, adequate sanitation access, poor population, and average school age to analyze life expectancy in Indonesia from 2017 to 2021 using the random effect model approach. Resa and Aprirachman [7] utilized the variables health facilities, health energy, and gross regional domestic product to analyze life expectancy in the NTB province from 2019 to 2021 through panel regression techniques. Alwi et al. [8] undertook an investigation in South Sulawesi in 2019, analyzing the impact of clean and healthy living behavior, undernourishment, and average school age on LEI using multiple regression analysis.

Previous research conducted by Ramadhani et al. [4], Mukrom et al. [5], Septianingsih [6], Resa and Aprirachman [7], and Alwi et al. [8] indicate that average school age, poor population, and per capita expenditure are key factors influencing the LEI. Therefore, this study used the average school age, the poor population, and per capita spending as independent variables to analyze the LEI in the province of NTB. In addition, the independent variables in this study are selected based on the data available from the BPS of NTB.

Previous scholars utilized spatial analysis, multiple regression with cross-section data, and panel regression to investigate the determinants influencing LEI. Gujarati and Porter [9], Astuti [10], Astuti et al. [11], [12] suggest that panel regression is more effective in analyzing dynamic changes by properly identifying and quantifying effects than to doing regression solely on time series or cross-sectional data. Panel data offers more useful data with increased degrees of freedom, reduced correlation among variables, and enhanced efficiency. Consequently, this study utilizes panel regression methods to analyze LEI in the NTB province from 2011 to 2020. Furthermore, panel regression is utilized since the calculation of LEI in the NTB province per year involves an aggregation of data from 10 districts/cities within the province. Merely analyzing LEI in the NTB province using cross-sectional data is insufficient; temporal (time series) factors must also be considered. The small number of districts/cities in the province of NTB has led to issues in measuring factors linked to determining degrees of freedom.

The primary distinctions between this study and prior research are the time periods and independent variables. The analysis covers the time frame from 2011 to 2020. The study included a unique independent variable that has not been utilized by prior researchers, which includes the average age of school, per capita expenditure, and the poor population number simultaneously. The essay commences by elucidating the rationale behind examining life expectancy data in NTB using panel regression techniques. Section 2 explains the theory behind using research methods. Section 4 presents the outcome of analysis and discussion. Section 5 is dedicated to conclusions and suggestions.

II. LITERATURE REVIEW

A. *Life Expectancy Index*

The Life Expectancy Index (LEI) is the average number of years a person who has reached a specific age in a particular year is expected to live, based on the current mortality rates in the community [13]. The LEI is a metric used to assess government effectiveness in enhancing the overall welfare of the people and specifically in improving health outcomes. Studying LEI in a region is crucial to identify the factors influencing life expectancy, enabling the local government to implement a program aimed at improving the region's life expectancy.

The LEI is a measure of public health that mirrors the effectiveness of health development. A higher LEI indicates a higher level of public health, which is reinforced by achievements in health sector progress. Unsuccessful health development results in a poor level of public health, leading to a low Life Expectancy [14].

Life expectancy at birth is a crucial metric for assessing the health and well-being of a population. Life expectancy at birth is a measure used to predict the average lifespan of individuals at a specific time or age group. Low life expectancy may indicate a poor quality of life. An arise in life expectancy can indicate enhancements in quality of life and advancements in a nation's health and social infrastructure.

Life expectancy at birth is determined by analyzing statistical data gathered from a population or country during a specific timeframe. Life expectancy is calculated using an indirect estimating method that involves two categories of data: children born alive and children currently alive [15]. The life expectancy index is determined using United Nations Development Programme (UNDP) standards, with a range from 25 years as the minimum value to 85 years as the maximum value.

B. *Panel Regression*

Panel data regression is a regression that uses panel data, which is a combination of cross section data and time series data [9], [11], [12], [16] . Cross section data can be individuals, households, companies, countries, or other entities observed at a certain point in time. Time series data can be daily, weekly, monthly, quarterly, annually, or in other time intervals. Panel data regression uses data in the form of observations of cross section units repeatedly over several time periods. In general, the panel data regression model can be seen in equation (1).

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

where t is the t-th period (t =1, 2, ..., T), i is the i-th observation unit (i =1, 2, ..., N), k is the independent variable being tested (n =1, 2, ..., n), Y_{it} is the dependent variable at the i-th observation unit and time t, X_{kit} is the independent variable at the i-th observation unit and the t-th time, β_0 is a constant/intercept, β_k is the parameter for the nth variable, ε_{it} is the error in the i-th observation unit and the t-th period [17], [18].

C. *Approach and Estimation of Panel Data Regression Model*

1) *Common Effect Model* (CEM)

The CEM model is the simplest technique in estimating panel data because it only combines time series and cross section data. This model does not pay attention to the individual or time dimension so that it is assumed that the behavior between individuals is the same in various periods of time. This model can be estimated using the Ordinary Least Square (OLS) approach [10], [19]. The CEM model is written in equation (2).

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

Where, $\mathrm{Y_{it}}$ is the dependent variable at the i-th observation unit and t-th time, β_0 is a constant/intercept, β_k is the parameter for the k-th variable, X_{it}^k is the j-th independent variable of the i-th individual at time t, i is the cross section unit, t is the time series unit, εit is the error at the i-th observation unit and time t, k is many independent variables.

2) *Fixed Effect Model* (FEM)

This model is used to overcome the weaknesses of the CEM model. FEM models show differences in constants between objects, even with the same regressor coefficients [19]. FEM is a model that assumes that the intercept coefficient is different for each individual. In the FEM model, dummy variables are used to explain the intercept coefficient for each individual. To estimate this FEM, the Least Square Dummy Variable method is used [20]. FEM is written in equation (3).

$$Y_{it} = \beta_{0_i} + \beta_j X_{it}^j + \sum_{i=2}^{n} a_i D_i + \varepsilon_{it} \quad (3)$$

Where, Y_{it} is the dependent variable at the i-th observation unit and t-th time, β_i is the i-th individual intercept, β_k is the parameter for the k-th variable, X_{it}^j is the j-th independent variable of the i-th individual at time t, D_i is a dummy variable, ε_{it} is the error at the i-th observation unit and time t.

3) *Random Effect Model* (REM)

This model will estimate nuisance variables that may be interconnected across time and individuals. The advantage of using this model is that it can eliminate heteroscedasticity. This model is also called the Error Component Model (ECM) or Generalized Least Square (GLS) [21]. The REM equation can be seen in equation (4).

$$Y_{it} = \beta_0 + \beta_j X_{it}^j + \varepsilon_{it};\ \varepsilon_{it} = u_i + V_t + W_{it} \quad (4)$$

Where, Y_{it} is the dependent variable at the i-th observation unit and t-th time, β_0 is the intercept, β_k is the parameter for the k-th variable, X_{it}^k is the j-th independent variable of the i-th individual at time t, ε_{it} is the error at the i-th observation unit and time t, u_i is the cross-section error component, V_t is the time series error component, and W_{it} is the combined error component.

D. *Panel Data Regression Model Selection*

1) *Chow Test*

The Chow test is used to choose between CEM and FEM through the residual sum squares value [22]. 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).

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

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

Decision:

If p-value ≤ α, then the initial hypothesis (H_0) is rejected, which means that the selected model is FEM. If p-value > α, then the initial hypothesis (H_0) is accepted, which means that the selected model is CEM.

2) *Hausman Test*

This test is used to choose between the REM or FEM model. To determine the Random Effect Model, assumptions can be made about the correlation between the components of the residuals and the independent variables. If it is assumed that there is no correlation between the residuals and the independent variables, then the appropriate model is REM. If on the contrary, then the appropriate model is FEM [21].

Hypothesis:

H_0: *Random Effect Model* (REM)

H_1: *Fixed Effect Model* (FEM)

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

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

Where, $\hat{\beta}_{FEM}$ is the coefficient vector of independent variables from FEM, $\hat{\beta}_{REM}$ is the coefficient vector of independent variables from REM.

Decision:

If p-value ≤ α, then the initial hypothesis (H_0) is rejected, which means that the selected model is FEM. If p-value > α, then the initial hypothesis (H_0) is accepted, which means that the selected model is REM.

3) *Lagrange Multiplier (LM) Test*

The LM test is used to select a better model between CEM and REM, by conducting REM testing based on the residual value εit from CEM[21].

Hypothesis:

H_0: *Common Effect Model* (CEM)

H_1: *Random Effect Model* (REM)

The value of the LM test statistic 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 the number of individuals, T is the number of time periods, and ε_{it} is the combined model residual

Decision:

If p-value ≤ α, then the initial hypothesis (H_0) is rejected, which means that the selected model is REM. If p-value > α, then the initial hypothesis (H_0) is accepted, which means that the selected model is CEM.

E. *Panel Data Regression Model Assumption Test*

1) Multicollinearity Test

The multicollinearity test is carried out with the aim of assessing whether there is a correlation between the independent variables in this regression model. This method is used to identify the presence of multicollinearity problems by evaluating the simple correlation value between the independent variables. This assumption requires variables to have a Variance Inflation Factors (VIF) value smaller than 10. A VIF value greater than 10 indicates a multicollinearity problem in the research model [9], [18].

2) Heteroscedasticity Test

This test aims to test whether there is a difference in the variance of the residuals between one observation and another in the regression model [9] . Heteroscedasticity can be seen using the white method. The white test aims to identify whether the residual variance is not constant. The method commonly used in the white test is to regress the squared residuals against all explanatory variables in the model [23]. If the probability value (p-value) is smaller than 0.05 (significance value) then there is a heteroscedasticity problem.

F. *Parameter Testing or Regression Feasibility*

1) Partial Test (*t* Test)

Partial tests are used to test whether the independent variable (individually) affects the dependent variable. The *t*-test statistical formula used can be seen in equation (8).

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

The hypothesis used in the t test is:

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

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

Decision:

If p-value ≤ α, then H_0 rejected, which means that the independent variable has a partially significant effect on the dependent variable in the model. If p-value > α, then H_0 is accepted, which means that the independent variable has no partially significant effect on the dependent variable in the model.

2) Simultaneous Test (*F* Test)

Simultaneous test or F test is conducted to determine the effect of independent variables on the dependent variable [9], [17]. With the test statistic written in equation (9).

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

Where, R^2 is *R-Square* (squared correlation coefficient), K is the number of independent variables including constants, N is the number of samples.

The hypothesis used in the *F* test is:

H_0: $\beta_1 = \beta_2 = \beta_3 = 0$, the independent variable does not simultaneously have a significant effect on the dependent variable

H_1: $\beta_1 \neq \beta_2 \neq \beta_3 \neq 0$, the independent variable simultaneously has a significant effect on the dependent variable

Decision:

If p-value ≤ α, then H_0 rejected, which means that the independent variables simultaneously have a significant effect on the dependent variable in the model. If p-value > α, then H_0 is accepted, which means that the independent variables do not simultaneously have a significant effect on the dependent variable in the model.

3) Coefficient of Determination

The coefficient of determination (Adjusted R-Square) is used to measure how much the independent variable can explain the dependent variable. If the coefficient of determination is close to 1, the effect of the independent variable on the dependent variable is strong, and if the coefficient of determination is 0, the independent variable has no effect on the dependent variable [22]. With the test statistics written in equation (10).

$$KD = R^2 \times 100\% \qquad (10)$$

where, *KD* is the Coefficient of Determination, R^2 is *R-Square* (squared multiple correlation coefficient).

III. METHODOLOGY

A. Variables, Type, and Data Source

This study accommodates life expectancy index (LEI) as a dependent variable. Average years of school (AYS), per capita expenditure adjusted (ACE), and the number of poor people (NPP) were the independent variables. The research technique utilized secondary data from the BPS of West Nusa Tenggara, which can be accessed at https://ntb.bps.go.id/. The panel data consists of time series data from 2011 to 2020 and cross-sectional data from 10 districts/cities in West Nusa Tenggara province, namely: West Lombok, East Lombok district, Central Lombok district, North Lombok district, Sumbawa district, West Sumbawa district, Bima district, Dompu district, Bima city, and Mataram city.

B. Model Specifications

This study aims to model the life expectancy of NTB province from 2011 to 2020 using panel data regression. There are 3 (three) independent variables used, namely; average years of schooling, adjusted per capita expenditure, and the number of poor people. The regression equation or model in this study can be seen in equation (11).

$$\ln \mathrm{LEI}_{it} = \beta_0 + \beta_1 \ln \mathrm{AYS}_{it} + \beta_2 \ln \mathrm{ACE}_{it} + \beta_3 \ln \mathrm{NPP}_{it} + \varepsilon \qquad (11)$$

where, t is the t-th period (t =2011, 2011, ..., 2022), i is the i-th observation unit (i =1, 2, ..., 10), $\boldsymbol{\beta_0}$ is a constant/intercept, $\boldsymbol{\beta_1}, \boldsymbol{\beta_2}, \boldsymbol{\beta_3}$ is the independent variables parameter, and ε is error.

C. Analysis Phase

The detailed stages of panel data regression analysis based on the data analysis flow are presented as follows:

1. Preparing the data, namely: ensuring that the data to be used has been collected and is available in panel data format. The data used in the analysis process is data that has been logarithmically naturalized because it follows the working principle of the Cobb-Douglas function.
2. Identify and define dependent and independent variables.
3. Exploring data, namely; knowing the pattern of correlation between variables through scatterplots and analyzing descriptively.

4. Selecting a regression model: determining the type of regression model that is appropriate for the research problem. Panel data regression models may include CEM, FEM or REM. The test can be conducted randomly, so it does not have to start with the Chow test.
5. Conduct classical assumption tests, namely: checking the assumptions required for panel data regression models, namely multicollinearity and heteroscedasticity assumptions. If in step 3 the selected model is REM, then the heteroscedasticity test does not need to be performed. Because REM uses the Generalizes Least Squared (GLS) approach, which is useful for curing symptoms of heteroscedasticity so that the REM model is assumed to be free from symptoms of heteroscedasticity [24]. The linearity test is not used because the model is assumed to be linear, and the normality test is basically not a requirement for the Best Linear Unbiased Estimator (BLUE**)** [19]. If there is a violation of these assumptions, it is necessary to consider transforming the variables.
6. Estimating parameters, namely: using the panel data regression method to obtain the coefficients of each variable used to model LEI.
7. Interpreting results.

IV. RESULTS AND DISCUSSIONS

1. Research Variables Correlation

The correlation between the variables of the study, i.e. life expectancy, average school age, 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 right, rising. The correlation values or relationships between variables are presented in Table 1.

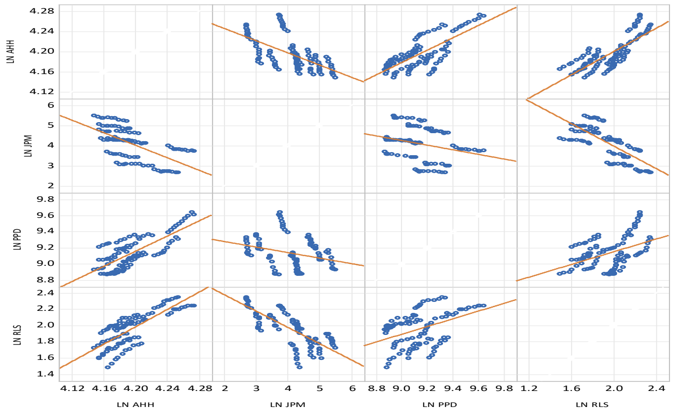

Figure 2. Scatterplot of research variables correlation

Average years of school (AYS) and adjusted per capita expenditure (ACE) have a positive impact on life expectancy index. However, the number of poor people (NPP) has a negative impact on the life expectancy (LEI). This means that NTB provinces with higher life expectant characteristics have a tendency to increase the average school age rate. Similarly, adjustable per capita expenditures are also positively linked to the lifespan rate. The number of poor people indicates a negative correlation with the life expectancy, which means that if the number of people in a district or city increases, then the life expected rate in that district/city will decrease.

Table 1. Correlation Matrix of Research Variables

	ln LEI	ln NPP	ln ACE	ln AYS
ln LEI	1.000	-0.612	0.756	0.784
ln NPP	-0.612	1.000	-0.279	-0.746
ln ACE	0.756	-0.279	1.000	0.431
ln AYS	0.784	-0.746	0.431	1.000

2. Panel Model Estimation

This study 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 2.

Table 2. Panel Data Model Estimation

Variable	**CEM**		**FEM**		**REM**	
	Coef.	***Prob.***	***Coef.***	***Prob.***	***Coef.***	***Prob.***
lnAYS	0.070	0.000	0.109	0.000	0.107	0.000
lnACE	0.083	0.000	0.064	0.000	0.072	0.000
lnNPP	-0.004	0.081	-0.012	0.165	-0.003	0.585

Table 1 informs that in the common effect, fixed effect, and random effect models, average years of schooling (ln AYS) and adjusted per capita expenditure (ln ACE) have a significant effect on life expectancy index (ln LEI). However, the number of poor people (ln NPP) has a negative and insignificant effect on life expectancy index (ln LEI). This is because the Prob. value > 0.05 or 0.585 > 5%.

3. Panel Model Selection

There are 3 tests conducted 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.

a. Chow Test

The Chow test results are presented in Table 3, which informs that the Prob. Cross-Section F is 0.000. This value is smaller than the significance level used, which is 5% or 0.000 < 0.05, which results in H_0 being rejected. Therefore, the chosen model is the Fixed Effect Model.

Table 3. *Chow* Test Results

Effect Test	*Statistic*	*d.f.*	*Prob.*	**Decision**
Cross-section F	186.52	9.87	0.000	H_0 is rejected

b. Hausman Test

The Hausman test results are presented in Table 4, which informs that the Prob. Cross-Section Random is 0.3619. This value is greater than the significance level used, which is 5% or 0.3619 > 0.05, which results in H_0 being accepted. Therefore, the selected model is the Random Effect Model.

Table 4. Hausman Test Result

Test Summary	*Chi-Sq. Statistic*	*Chi-Sq. d.f.*	*Prob.*	**Decision**
Cross-section Random	3.199	3	0.3619	H_0 is not rejected

c. Lagrange multiplier Test

The Lagrange Multiplier test results are presented in Table 5, which informs that the Prob. Cross-section Breusch-Pagan value of 0.000. This value is smaller than the significance level used, which is 5% or 0.000 <0.05, which results in H_0 being rejected. Therefore, the selected model is the Random Effect Model.

Table 5. *Lagrange Multiplier* Test Result

	Cross-section	*Time*	*Both*	**Decision**
Breusch-Pagan	384.0917 (0.0000)	2.519364 (0.1125)	386.6111 (0.0000)	H_0 is rejected

The estimation results of the panel model selection show that the best panel model to model life expectancy in NTB province in 2011-2020 is the Random Effect Model, which can be seen in equation (12).

$$\ln \widehat{LEI}_{\mathrm{it}} = 3{,}335 + 0{,}107 \ln AYS_{\mathrm{it}} + 0{,}072 \ln ACE_{\mathrm{it}} - 0{,}003 \ln NPP_{\mathrm{it}} \quad (12)$$

4. Classical Assumption Test

a. Multicollinearity Test

The multicollinearity test results of the regression model are presented in Table 6. Based on Table 6, there is no variable has a VIF value more than 10 [25], meaning that all independent variables in this study do not experience multicollinearity problems.

Table 6. Multicollinearity Test Result

Variable	**R**	**R^2**	***Tolerance***	**VIF**
ln AYS	0.431	0.186	0.814	2.121
ln ACE	-0.747	0.558	0.442	1.291
ln NPP	-0.279	0.078	0.922	1.769

b. Heteroscedasticity Test

In this case, the heteroscedasticity test is not performed, as the selected model is the Random Effect Model. Random effect models naturally overcome the problem of heteroscedasticity by including fixed effects for each unit of observation. Therefore, no additional heteroscedasticity test is required.

5. Parameter Significance Test

The parameter significance test conducted in this study consists of a partial test (t test), simultaneous test (F

test), and coefficient of determination test (R^2). The following are the results of the three tests.

a. Partial Test (*t* Test)

The t-test results for the Random Effect Model are presented in Table 7.

Table 7. Partial Test Result (*t*-Test)

Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
Constant	3.335	0.070	47.375	0.000
ln AYS	0.107	0.009	11.609	0.000
ln ACE	0.072	0.007	9.767	0.000
ln NPP	-0.003	0.005	-0.546	0.585

We will elucidate the relationship between each independent variable and the dependent variable in the upcoming discussion.

1) Constant

Unaccounted factors can impact the consistent output of the model. The p-value of the constant is 0.000. The value is less than the significance level (α = 5%), or 0.000 < 0.05. Null hypothesis is rejected. Other variables in the model significantly impact life expectancy figures.

2) Examining the impact of the average school age on life expectancy in NTB province.

Table 7 displays the value of the average years of school, which is 0.107, and its corresponding p-value of 0.000. The p-value is less than the significance level (α = 5%), specifically 0.000 < 0.05. Thus, we refute the null hypothesis. The average school age significantly influences the life expectancy rate in the NTB province. An individual's average age during their time in school positively impacts their longevity if all other things being equal.

Between 2011 and 2020, the average school age positively and significantly impacted life expectancy in the NTB province. Ramadhani, et.al [4] did research that is in line with this study. Mukrom, et al. [5] and Alwi, et al. [8] also suggested the same proposal. The average school experience significantly influences the foundation of knowledge, behavior, and health access, ultimately impacting life expectancy.

3) Analyzing the influence of adjusted per capita expenditure on life expectancy in the NTB province.

In Table 7, the adjusted per capita expenditure coefficient is 0.072, and the adjustable per capita expenditures probability value is 0.000. The p-value is less than the significance level (α = 5%), or 0.000 < 0.05. We refuse the null hypothesis. Partially, adjusted per capita expenditure significantly affects the life expectancy rate in the NTB province. The favorable effect of adjusted per-capita expenditures on lifespan rate is significant if all other things being equal.

This study aligns with the research conducted by Nurfitri and Yanti [26]. Adjusted per capita spending is a metric utilized to assess purchasing power as a key indicator of a satisfactory level of living. Improving education and health services is a direct outcome of allocating resources effectively and ensuring the availability of quality health facilities. This, in turn, boosts public income and allows for better access to healthcare services. Adjusted per capita spending positively impacts average household health by addressing economic disparities and ensuring equitable access to health benefits for all populations.

4) Analyzing the correlation between poverty and life expectancy in NTB province.

Table 7 shows that the coefficient value for the number of poor people is -0.003, with a p-value is 0.585. The p-value is bigger than the significance level (α = 5%), indicating that the result is not statistically significant. Thus, the null hypothesis (H_0) is accepted. The impoverished population of the NTB province does not have a substantial impact on life expectancy.

The quantity of impoverished individuals has an adverse, albeit statistically insignificant, effect on life expectancy. An increase in the number of individuals will result in a fall in the life expectancy rate. While the impoverished population may be somewhat dissatisfied, when considered alongside other independent variables like average school duration and adjusted per capita spending, it can have a notable impact on the expected lifespan. Ramadhani, et. al [4], Mukrom, et. al. [5], and Septianingsih [6] indicates that the quantity of impoverished individuals has a notable impact on life expectancy. The study shows that economic disparities can negatively impact public health, leading to notable variations in life expectancy rates between impoverished individuals and wealthier ones.

b. Simultaneous Test (*F* Test)

The results of the F test with the Random Effect Model are presented in Table 8.

Table 8. *F* Test Result of Research Variables

Statistics	Value	Statistics	Value
R-squared	0.948	*Mean dependent var*	0.253

Adjusted R-squared	0.946	*S.D. dependent var*	0.012
S.E. of regression	0.002	*Sum squared resid*	0.000
F-statistic	588.320	*Durbin-Watson stat*	0.640
Prob(F-statistic)	0.000		

The test results using the Random Effect Model in Table 8 inform that the Prob (*F-statistic*) value is 0.000, where this value is less than the significance level $\alpha = 0.05$, or $0.000 < 0.05$, which means that H_0 is rejected. Thus, it can be concluded that the average years of school, adjusted per capita expenditure, and the number of poor people simultaneously have a significant effect on life expectancy in NTB province.

c. Coefficient of Determination

The results of the analysis in Table 3.8 inform us that the R-squared value is 0.948, which indicates that changes in life expectancy in NTB province by 94.80% can be explained by the average years of schooling, adjusted per capita expenditure, and the number of poor people. While the remaining 5.20% is explained by other variables not used in this study.

The analysis indicates that the average school age, adjusted per capita expenditure, and the percentage of poor individuals collectively have a substantial impact on life expectancy. This concurrent impact demonstrates the intricate interplay among these elements. The adverse effects of a large impoverished population can be counterbalanced by the beneficial influence of other factors. Even while not fully evident, the number of impoverished inhabitants remains substantial when considered alongside other variables. In this scenario, intensifying efforts to decrease the population size continues to be important for raising the average life expectancy.

V. CONCLUSIONS AND SUGGESTIONS

The conclusions drawn on the results of the analysis and discussion are as follows. a) The average length of schooling partially has a positive and significant effect partially on life expectancy in NTB province from 2011 to 2020. The higher the average number of years of schooling, the higher the life expectancy. b) The partially adjusted per capita expenditure has a positive and significant effect partially on life expectancy in NTB province from 2011 to 2020. The higher the adjusted per capita expenditure, the higher the life expectancy. **c)** The number of poor people partially has a negative and insignificant influence on life expectancy in NTB province from 2011 to 2020. If the number of poor people increases, then life expectancy decreases. d) The average years of schooling, adjusted per capita expenditure, and the number of poor people simultaneously have a significant effect on life expectancy in NTB province from 2011 to 2020.

Suggestions for increasing life expectancy in West Nusa Tenggara Province for the Government are to take a policy by minimizing the improvement of the quality of life of the community and advancing the health and social systems of the community. To future researchers, in the development of science it is recommended to conduct research on life expectancy by adding or using other independent variables. In addition, it is expected to study life expectancy in more detail in each regency/city by adding spatial studies, so that it becomes a consideration for the government in determining human resource development policies.

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