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ORDINAL PROBIT REGRESSION MODELING ON THE HUMAN DEVELOPMENT INDEX MALUKU AND NORTH MALUKU PROVINCES

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Abstract

This study examines the factors influencing Human Development Index (HDI) in Maluku and North Maluku Provinces using ordinal probit regression. Secondary data are employed to identify key socio-economic variables affecting HDI levels. Model selection is based on the Akaike Information Criterion (AIC), Schwarz Bayesian Information Criterion (SBIC), and R^2 values, while the Likelihood Ratio (LR) test is used to evaluate the significance of parameters. The findings reveal that expected years of schooling (X_2) is the most significant factor in determining HDI categories. The model that includes only this variable yields the lowest AIC and SBIC values and shows a significant LR test result. Furthermore, the negative regression coefficient indicates that an increase in expected years of schooling raises the probability of a region achieving a higher HDI category. These results underscore the crucial role of education policies in promoting human development. Future research is encouraged to incorporate economic, health, and infrastructure variables to provide a more comprehensive understanding of the factors influencing HDI.

Keywords: *AIC, Expected years of schooling, Human Development Index, Ordinal probit regression, SBIC.*

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1. INTRODUCTION

The Human Development Index (HDI) is a primary indicator for assessing the success of regional development in terms of education, health, and the economy [1]. The government utilizes HDI as a basis for designing policies to improve public welfare [2]. However, there are significant disparities in HDI achievement among provinces in Indonesia, particularly between the western and eastern regions. Maluku and North Maluku, as part of eastern Indonesia, continue to face challenges in improving HDI due to limited access to education, healthcare services, and economic infrastructure.

According to a report by the Central Bureau of Statistics (BPS), HDI in Maluku and North Maluku is relatively low compared to other provinces in Indonesia [3]. Moreover, many districts and cities within these provinces are categorized as frontier, outermost, and least developed regions (3T). This geographical and developmental context highlights the urgency to better understand the underlying factors that significantly influence HDI in these areas. Thus, the research gap addressed in this study is the lack of specific and recent empirical analysis on the determinants of HDI in Maluku and its surrounding regions.

This study aims to identify the most influential factors affecting HDI in Maluku and North Maluku by analyzing indicators such as expected years of schooling, poverty levels, and life expectancy [4]. The findings are expected to offer practical insights into the conditions of human development in these provinces and to identify which variables contribute most significantly to HDI improvement. This can serve as a valuable input for policymakers to design more effective, data-driven strategies tailored to the unique challenges of these regions.

Based on this background, this research focuses on three main questions: (1) Do education, health, and economic factors significantly influence HDI in Maluku and North Maluku? (2) Which factor has the most dominant impact on improving HDI in these regions?. The objectives of this study are: (1) To analyze the impact of expected years of schooling, poverty levels, and life expectancy on HDI; (2) To identify the variables that have the most significant effect on HDI improvement.

The novelty of this research lies in the application of the ordinal probit regression model to analyze the factors influencing HDI in regions categorized as 3T, which has not been widely explored in previous studies. While some studies have applied similar models in other provinces—such as Nazillah in East Java [5], and Dwiningtias and Mahmudah in Central Java [6]—there is a lack of focus on eastern Indonesia. The ordinal probit model is well-suited for capturing the relationship between predictors and an ordinal outcome variable [7], as also demonstrated in studies like that of Cahyati, Herrhyanto, and Puspita (2019) on the Gender Development Index [8]. Through this study, policymakers in Maluku and North Maluku will gain a clearer, evidence-based understanding of human development conditions and be better equipped to formulate interventions that directly address regional disparities.

2. METHODOLOGY

2.1. Data Sources

This study uses secondary data from the Central Bureau of Statistics (BPS) on the Human Development Index (HDI) in Maluku and North Maluku [9]. The dataset includes key education, health, and economic indicators collected from 2023 to 2024. While BPS data is generally reliable, potential limitations include inconsistent update cycles, limited coverage in remote areas, and possible underreporting in 3T (underdeveloped, frontier, and outermost) regions. These factors may introduce bias that could influence model accuracy and are carefully considered in the interpretation of the results.

2.2. Research Variables

The variables used in this study are categorized as follows:

- Dependent Variable: The Human Development Index (HDI), categorized on an ordinal scale.
- Independent Variable:
  - Education: Measured by the expected years of schooling (EYS) and the average years of schooling (AYS).
  - Health: Measured by life expectancy (LE).
  - Economy: Measured by the percentage of the poor population (PP) and Gross Regional Domestic Product (GRDP) per capita.

2.3. Sampling Technique

The sample includes HDI, education, health, and economic data from all regencies/cities in Maluku and North Maluku [10] [11].

2.4. Analysis Method

This study employs ordinal probit regression to analyze the relationship between independent variables and HDI as the dependent variable [12]. Ordinal probit regression is chosen because it can capture the relationship between ordinal categorical variables and independent variables that are either continuous or categorical [13]. The analysis follows these stages [14] [15]:

- Descriptive Statistics: Provides an overview of the dataset and tests data normality.
- Model Testing: Validates the ordinal probit regression model using R^2 and AIC criteria.
- Parameter Estimation: Determines the influence of each variable on HDI.
- Interpretation: Identifies the dominant factors and policy implications based on the analysis findings.

3. RESULTS AND DISCUSSION

Based on the test results, it was found that the Human Development Index (HDI) of Maluku and North Maluku provinces follows a normal distribution, as indicated by a P-Value of 0.059, which is greater than 0.05. So the ordinal probit regression model was chosen due to its assumption of normally distributed error terms, which aligns well with the characteristics of the HDI data in this study.

Table 1. Percentage of Regency/Municipality Groups in Maluku and North Maluku Provinces

Categori	Maluku and North Maluku	
	Count	Percentage (%)
Low	14	66,67
Medium	5	23,80
High	2	0,083

Source: Eviews 11

According to **Table 1**, the majority of regencies/cities in Maluku and North Maluku fall into the low HDI category, accounting for 66.67% of the total areas analyzed. Only 8.33% of the regions have a high HDI, while 23.80% fall into the medium category. This distribution highlights the existing development disparity in these two provinces, where most regions face challenges in economic, educational, and health aspects.

Table 2. Descriptive Statistics by HDI Category

Variable	Low		Medium		High	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Percentage of Poor Population (X1)	14.244	8.277612	16.75	6.258008	4.32	1.315219
Expected Years of Schooling (X2)	12.922	0.341657	13.95	0.511547	15.925	0.205061
Life Expectancy (X3)	69.95	1.258992	71.08	0.742718	72.705	0.219203
Per Capita Expenditure (X4)	7970.2	842.3795	9570	1283.534	14367	459.6194

Source: Eviews 11

From **Table 2**, it is evident that regions with high HDI have better economic well-being, education, and healthcare compared to regions with low HDI. Regencies/cities with high HDI have the highest average per capita expenditure, amounting to Rp14,367 thousand with a small standard deviation (Rp459.62 thousand), indicating better economic stability. Conversely, regions with low HDI have an average per capita expenditure of Rp7,970.29 thousand with a larger standard deviation (Rp842.38 thousand), reflecting a higher level of economic inequality. Additionally, the percentage of the poor population in low-HDI regions reaches 14.24%, significantly higher than in high-HDI regions, which is only 4.32%, indicating that poverty is a major factor in HDI disparities.

Apart from economic factors, education and healthcare also play a significant role in determining HDI levels. Regions with high HDI have an average expected years of schooling of 15.93 years, higher than the 12.92 years in low-HDI regions. Meanwhile, life expectancy is also higher in high-HDI regions (72.71 years) compared to low-HDI regions (69.95 years). These results suggest that investment in education and healthcare is a key factor in improving the quality of life. Therefore, increasing HDI in Maluku and North Maluku should focus on poverty reduction, improving access to education, and enhancing healthcare services to achieve more equitable and sustainable development.

3.1. Probit Regression Model with R^2 Criterion

A partial parameter test was conducted to evaluate the influence of each predictor variable on HDI in Maluku and North Maluku provinces. The significance level used was 0.05, with the critical region for rejecting H_0 being $|Z| > 1.96$ or using $p-value \leq 0.05$.

Table 3. Partial Parameter Significance Test

Variable	Coefficient	Std. Error	Z-Value	Decision
X1	-0.03212	0.03638	-0.88282	Accept H0, statistically insignificant
X2	3.362576	1.365422	2.462665	Reject H0, statistically significant; contributes positively to HDI
X3	1.314465	0.46186	2.846021	Reject H0, statistically significant; contributes positively to HDI
X4	0.000976	0.000337	2.901756	Reject H0, statistically significant; contributes positively to HDI

Source: Eviews 11

The partial test results indicate that X_2 (expected years of schooling), X_3, and X_4 significantly affect HDI, while X_1 is not significant.

Table 4. Results of Simultaneous Parameter Testing

Variable	Coefficient	Std. Error	P-value
X1	54.79507	77352575	1
X2	-5.89793	17843234	1
X3	0.011802	15283.54	1
X4	431.0188	8.62E+08	1
$\boldsymbol{\delta_1}$	505.319	8.96E+08	1
$\boldsymbol{\delta_2}$	54.79507	77352575	1

Source: Eviews 11

Based on the simultaneous test, the likelihood ratio (LR) test is used to compare the fit of the full model with a restricted mode, significant LR statistic indicates that the model with predictors fits the data better, supporting the relevance of the included variables. The LR value was 35.10937, which is greater than the critical value of 7.815, meaning that at least one variable is significant. However, since all variables have a p-value > 0.05, model does not exhibit a significant simultaneous effect.

Table 5. Pseudo R^2 Values of Each Model

Variable	*Pseudo* R2 (%)
X2	77,12
X3	39,32
X4	57,58

Source: Eviews 11

The best model was selected based on the highest Pseudo R^2 value, which is the model with the X_2 (expected years of schooling) variable at 77.12%.

3.2. Probit Regression Model with AIC and SBIC Criteria

Based on the analysis using EViews, the best ordinal probit regression model was determined based on the Akaike Information Criterion (AIC) and Schwarz Bayesian Information Criterion (SBIC). Model with AIC = 0.6682 and SBIC = 0.8174 includes only the variable of expected years of schooling (X_2).

Table 6. Parameter Testing Results

Variabel	Coefficient	Std. Error	P-Value
$\boldsymbol{X_2}$	3.362576	1.365422	0.0138
$\boldsymbol{\delta_1}$	45.50183	18.24431	0.0126
$\boldsymbol{\delta_2}$	50.93699	20.73322	0.0140

Source: Eviews 11

Model validation was conducted using the Likelihood Ratio (LR) test, with the test results presented in **Table 6**. The results indicate that X_2 significantly influences the probability of districts/cities in Maluku and North Maluku Provinces attaining a low, medium, or high Human Development Index (HDI). This is supported by an LR statistic of 27.07587, which exceeds the critical value of 3.814.

The strong influence of expected years of schooling on HDI outcomes is consistent with findings from previous studies. For instance, Nazillah's research on East Java highlighted that education, particularly the level of schooling, was the dominant factor affecting HDI [5]. Similarly, Dwiningtias and Mahmudah found that human capital factors, especially education and health, had significant impacts on HDI levels [6]. Theoretically, education is one of the core components of the HDI calculation, alongside health and standard of living, making it a fundamental driver of human development.

Expected years of schooling serves as a forward-looking measure of the education system's ability to provide future generations with access to learning opportunities. Higher expected years of schooling indicate better educational infrastructure and access, leading to improvements in knowledge, skills, and employability—key elements that enhance overall human capabilities.

Therefore, the best ordinal probit regression model, based on AIC and SBIC criteria, aligns with the selection results using Pseudo R^2, confirming that probit model including only the variable of expected years of schooling (X_2) is the most appropriate.

3.3. Final Probit Regression Model

The estimation results of the ordinal probit regression model reveal that the probability of a district/city falling into a specific HDI category is influenced by the expected years of schooling (X_2).

$$\hat{P}(Y=0) = \phi(45{,}50183 - 3{,}362576\, X_2) \quad (1)$$

$$\hat{P}(Y=1) = \phi(50{,}93699 - 3{,}362576\, X_2) - \phi(45{,}50183 - 3{,}362576\, X_2) \quad (2)$$

$$\hat{P}(Y=2) = \phi(50{,}93699 - 3{,}362576\, X_2) \quad (3)$$

Equation (1) represents the probability of a low HDI (Y=0) as the cumulative standard normal distribution function with a threshold of 45.50183 minus the effect of X_2. **Equation (2)** describes the probability of a medium HDI (Y=1) as the difference between two cumulative normal distribution functions at the thresholds of 50.93699 and 45.50183, depending on X_2. Meanwhile, **Equation (3)** states the probability of a high HDI (Y=2) as the cumulative normal distribution function at the highest threshold.

The regression coefficient of -3.362576 for X_2 indicates that an increase in expected years of schooling reduces the probability of a district/city having a low HDI and increases the probability of being in a higher HDI category. The threshold values of 45.50183 and 50.93699 serve as cut-off points distinguishing HDI categories. These findings confirm that expected years of schooling is a significant determinant of human development levels in Maluku and North Maluku Provinces.

4. CONCLUSION

The results of this study demonstrate that expected years of schooling (X_2) is the most significant variable in determining the Human Development Index (HDI) category of districts/cities in Maluku and North Maluku. The ordinal probit regression model, which includes only this variable, yields the lowest Akaike Information Criterion (AIC), Schwarz Bayesian Information Criterion (SBIC), and R^2 values, indicating the best balance between model complexity and predictive accuracy. While AIC and SBIC provided useful model comparison criteria, future research could apply k-fold cross-validation to assess the generalizability of the model.

The positive regression coefficient suggests that an increase in expected years of schooling significantly increases the likelihood of an area moving to a higher HDI category. This implies that investments in education, particularly in improving access to and quality of education at all levels, are crucial for enhancing human development. Specifically, targeted educational investments—such as improving infrastructure in underserved areas, increasing the availability of trained teachers, and enhancing school facilities—could substantially boost expected years of schooling and, consequently, improve HDI.

Additionally, the significant Likelihood Ratio (LR) statistic confirms that the model is robust and suitable for policy analysis. Based on these findings, local governments should prioritize policies focused on enhancing educational opportunities, with a particular emphasis on remote and underserved regions. These investments in education can lead to long-term improvements in quality of life and overall human development.

Moreover, the methodology employed in this study, including the ordinal probit regression model, can be applied to other provinces in Indonesia or even similar regions in developing countries facing comparable challenges in improving HDI. This approach offers valuable insights for policymakers aiming to address disparities in human development across various regions.

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