p-ISSN 2338 – 3216
e-ISSN 2528 – 1070

JURNAL STATISTIKA
UNIVERSITAS MUHAMMADIYAH SEMARANG
12(2) 2024: 42-53

ORDINAL LOGISTIC REGRESSION MODEL FOR HUMAN DEVELOPMENT INDEX DATA IN PAPUA AND WEST PAPUA PROVINCES

Nabilla Rida Tri Nisa[1*], Novia Amilatus Solekha[2], Abdullah Fahmi[2], Panji Jilblathar[2], Purhadi[2]
[1] Department of Graphic Engineering, Faculty of Industrial Technology, Politeknik Negeri Media Kreatif, Srengseng Sawah Street, Jagakarsa Jakarta 12630 Indonesia
[2] Department of Statistics , Faculty of Science and Data Analytics, Institut Teknologi Sepuluh Nopember, Arief Rahman Hakim Street, Sukolilo Surabaya 60111 Indonesia

***e-mail**: *Nabilla.nisa@polimedia.ac.id*

Article Info:
Received: August 20th, 2024
Accepted: March 25th, 2025
Available Online: March 29th , 2025

Keywords:
Akaike Information Criterion (AIC), Human Development Index, Papua, West Papua, Ordinal Logistic Regression.

Abstract: The Human Development Index (HDI) is a key indicator used to measure the quality of economic development, particularly the degree of human development. In 2019, the HDI for Papua Province was 60.84, while West Papua Province recorded a value of 64.70. According to the Central Statistics Agency, these figures indicate that Papua and West Papua are the provinces with the lowest HDI in Indonesia. This research aims to identify the factors influencing the HDI in Papua and West Papua Provinces in 2019 using an ordinal logistic regression approach. The study utilizes secondary data from the Badan Pusat Statistik (BPS) for both provinces. The results indicate that the model developed is appropriate, with the Open Unemployment Rate (TPT) and average per capita expenditure being significant factors influencing HDI. The model's effectiveness is evidenced by an Akaike Information Criterion (AIC) value of 28.978.

1. INTRODUCTION

Development is a multifaceted process designed to enhance the well-being of people by addressing economic, social, cultural, and various other dimensions. To assess development performance, reliable indicators are necessary. These indicators are generally used to analyse and compare development achievements over time and across regions, with a focus on specific aspects [1][2][3].

The success of economic development in a region is closely tied to the process of human development, which is in turn influenced by the quality of the population. The Human Development Index (HDI) is a key indicator that measures the quality of human development in a region. The HDI focuses on three critical elements: health, education, and standard of living (often referred to as the economy). These elements are crucial in determining a province's ability to improve its HDI [4].

In 2019, the Province of DKI Jakarta had the highest HDI in Indonesia, while Papua and West Papua Provinces had the lowest. This disparity is largely attributed to the limited government efforts in enhancing development in education, economy, and health within Papua

[DOI: 10.14710/JSUNIMUS.12.2.2024.42-53]

and West Papua. However, these provinces are rich in natural resources, indicating potential for improvement in their HDI to be on par with other provinces.

Logistic regression is generally used when the dependent variable has two categories, but in some studies, the dependent variable can have more than two categories. In such cases, the analysis can be done with multinomial or ordinal logistic regression, depending on whether the dependent variable is sequential or not. To analyze ordinal variables, ordinal logistic regression is more appropriate. While multinomial logistic regression can be used for ordinal variables, employing ordinal logistic regression, which takes into account the ordered nature of the data, can enhance both the model's simplicity and its effectiveness [5][6][7].

Given this context, it is important to analyse the factors influencing HDI levels. HDI data is qualitative, categorized into three levels (high, medium, low), making it suitable for analysis using ordinal logistic regression. The findings of this research can assist the government in shaping future policy directions.

2. LITERATURE REVIEW

2.1. Ordinal logistic regression

Ordinal logistic regression is method used to examine the association between a dependent variable and one or more explanatory variables when the dependent variable is ordinal and consists of three or more distinct categories [8].

The ordinal logistic regression model is based on the cumulative logit model. This model is derived by comparing the cumulative probability with the probability of the outcome exceeding the j-th category versus the probability of it being greater than the j-th dependent category . The formula for the logit model in ordinal logistic regression is:

$$\text{Logit}\left[P(Y \le j|\mathbf{x})\right] = \ln\left[\frac{P(Y \le j|\mathbf{x})}{P(Y > j|\mathbf{x})}\right] = \ln\left[\frac{P(Y \le j|\mathbf{x})}{1 - P(Y \le j|\mathbf{x})}\right] = \beta_{0j} + \mathbf{x}^T\boldsymbol{\beta} \quad (1)$$

With $\beta_{01} < \beta_{02} < \cdots < \beta_{0j}$

If the dependent variable consists of 3 categories, then the ordinal logistic regression model formed is as follows [9]:

$$\text{Logit 1}\left[P(Y \le 1|\mathbf{x})\right] = \ln\left[\frac{P(Y \le 1|\mathbf{x})}{1 - P(Y \le 1|\mathbf{x})}\right] = \beta_{01} + \mathbf{x}^T\boldsymbol{\beta} \quad (2)$$

$$\text{Logit 2}\left[P(Y \le 2|\mathbf{x})\right] = \ln\left[\frac{P(Y \le 2|\mathbf{x})}{1 - P(Y \le 2|\mathbf{x})}\right] = \beta_{02} + \mathbf{x}^T\boldsymbol{\beta} \quad (3)$$

[DOI: 10.14710/JSUNIMUS.12.2.2024.42-53]

If there are three dependent categories, then the probability of each jth dependent category is:

$$\text{L}\,\pi_1(x) = \frac{\exp(\beta_{01} + \mathbf{x}_i^T \boldsymbol{\beta})}{1 + \exp(\beta_{01} + \mathbf{x}_i^T \boldsymbol{\beta})} \quad (4)$$

$$\pi_2(x) = \frac{\exp(\beta_{02} + \mathbf{x}_i^T \boldsymbol{\beta})}{1 + \exp(\beta_{02} + \mathbf{x}_i^T \boldsymbol{\beta})} - \frac{\exp(\beta_{01} + \mathbf{x}_i^T \boldsymbol{\beta})}{1 + \exp(\beta_{01} + \mathbf{x}_i^T \boldsymbol{\beta})} \quad (5)$$

$$\pi_3(x) = 1 - \frac{\exp(\beta_{02} + \mathbf{x}_i^T \boldsymbol{\beta})}{1 + \exp(\beta_{02} + \mathbf{x}_i^T \boldsymbol{\beta})} \quad (6)$$

The maximum likelihood method is used to estimate the parameters of a logistic regression model by finding the estimated value of **β** that maximizes the likelihood function [9]. The following is the likelihood function for a sample with n random samples.

$$l(\boldsymbol{\theta}) = \prod_{i=1}^{n} [\pi_1(\boldsymbol{x})^{y_{1i}} \pi_2(\boldsymbol{x})^{y_{2i}} \pi_3(\boldsymbol{x})^{1-y_{1i}-y_{2i}}]$$

From the likelihood function, the ln likelihood function is obtained as follows:

$$L(\boldsymbol{\theta}) = \sum_{i=1}^{n} [y_{1i} \ln \pi_1(\boldsymbol{x}) + y_{2i} \ln \pi_2(\boldsymbol{x}) + (1 - y_{1i} - y_{2i}) \ln \pi_3(\boldsymbol{x})]$$

The maximum ln-likelihood is obtained by differentiating $L\,(\boldsymbol{\theta})$ from $\boldsymbol{\beta_k}$ and equalizing zero. Maximum Likelihood Estimator (MLE) is a method used to estimate the variance and covariance of estimates of $\boldsymbol{\theta}$ obtained from the second derivative of the *ln-likelihood* function. The second derivative of the ln-likelihood function is obtained using the Newton Raphson iteration method. *Newton Raphson's* iteration formulation is as follows.

$$\boldsymbol{\theta}^{(t+1)} = \boldsymbol{\theta}^{(t)} - [\boldsymbol{H}(\boldsymbol{\theta}^{(t)})]^{-1} \boldsymbol{q}(\boldsymbol{\theta}^{(t)}) \quad (7)$$

Which,

$$\boldsymbol{q}(\boldsymbol{\theta}^{(t)}) = \left(\frac{\partial L(\boldsymbol{\theta})}{\partial \beta_{01}} \; \frac{\partial L(\boldsymbol{\theta})}{\partial \beta_{02}} \; \frac{\partial L(\boldsymbol{\theta})}{\partial \beta}\right)^T; \quad \mathbf{H}(\theta^{(t)}) = \begin{pmatrix} \frac{\partial^2 L(\boldsymbol{\theta})}{\partial \beta_{01}{}^2} & \frac{\partial L(\boldsymbol{\theta})}{\partial \beta_{01} \partial \beta_{02}} & \frac{\partial L(\boldsymbol{\theta})}{\partial \beta_{01} \partial \beta} \\ \frac{\partial L(\boldsymbol{\theta})}{\partial \beta_{01} \partial \beta_{02}} & \frac{\partial^2 L(\boldsymbol{\theta})}{\partial \beta_{02}{}^2} & \frac{\partial L(\boldsymbol{\theta})}{\partial \beta_{02} \partial \beta} \\ \frac{\partial L(\boldsymbol{\theta})}{\partial \beta_{01} \partial \beta} & \frac{\partial L(\boldsymbol{\theta})}{\partial \beta_{02} \partial \beta} & \frac{\partial^2 L(\boldsymbol{\theta})}{\partial \beta^2} \end{pmatrix}$$

with t being the 1st, *2,,t* iterations. The iteration stops if the convergent condition is met, namely the difference $\|\boldsymbol{\theta}^{(t+1)} - \boldsymbol{\theta}^{(t)}\| \leq \varepsilon$, which ε is a very small number.

[DOI: 10.14710/JSUNIMUS.12.2.2024.42-53]

2.2. Multicollinearity Assumtion

It is important to verify the multicollinearity assumption to determine if there are linear relationships or correlations between significant independent variables in the regression model. In ordinal logistic regression, multicollinearity is not acceptable. To detect multicollinearity, the Variance Inflation Factor (VIF) is used; a VIF value greater than 10 signals potential multicollinearity. The VIF is calculated using the following equation:

$$VIF = \frac{1}{1 - R_k^{\ 2}} \tag{8}$$

Where $R_k^{\ 2}$ is the coefficient of determination by regressing X $_k$ with other independent variables [13][15].

2.3. Hypothesis Testing

The model that has been obtained needs to be tested for significance by carrying out statistical tests including simultaneous tests and individual tests. Simultaneous tests were carried out to check the significance of the β coefficient on the dependent variables together using test statistics [10].

- Hypothesis :
  H_0 : $\beta_1 = \beta_2 = \cdots = \beta_p = 0$
  H_1 : there is at least one$\beta_k \neq 0;$
  $k = 1,2, \dots, p$
- Test statistics:

$$G^2 = -2\ln\left[\frac{L_0}{L_p}\right] \tag{9}$$

Information :

L_0 : maximum *likelihood value* from a function without independent variables
L_1 : maximum *likelihood value* of the function with all independent variables

- H_0 rejection area :
  $G^2 > \chi^2{}_{(\alpha,1)}$
- Decision to reject H $_0$:
  $G^2 hitung > \chi^2{}_{(\alpha,1)}$or $p - value < \alpha$.

Partial testing uses parameter tests This is done using the *Wald test statistic* (W). Wald test to find out significance of parameters to the dependent variable [10].

- Hypothesis:
  $H_0 : \beta_j = 0$
  $H_1 : \beta_j \neq 0; j = 1, 2, \dots, p$

[DOI: 10.14710/JSUNIMUS.12.2.2024.42-53]

- Test statistics:

$$W = \frac{\hat{\beta}_j}{SE(\hat{\beta}_j)} \tag{10}$$

$SE(\hat{\beta}_j)$ is the estimated standard *error* parameter.

- H_0 rejection area :
  $W > \chi^2_{(\alpha,1)}$
- Decision to reject H_0 :
  $W\ count > \chi^2_{(\alpha,1)}$ or value $p - value < \alpha$

2.4. Model Fit Test

Goodness-of-fit testing for tables is designed to evaluate how well the model represents the actual data [11]. Hypothesis used:

- Hypothesis :
  H_0 : The model is appropriate
  H_1 : The model is not appropriate
- Test Statistics:

$$D = -2\sum_{i=1}^{n}\sum_{j=1}^{J}\left[y_{ij} \ln\left(\frac{\hat{\pi}_{ij}}{y_{ij}}\right) + \left(1 - y_{ij}\right)\ln\left(\frac{1-\hat{\pi}_{ij}}{1-y_{ij}}\right)\right] \tag{11}$$

with:

$\hat{\pi}_{ij} = \hat{\pi}_j(\boldsymbol{x_i})$ are *the* ith and jth observation *opportunities*

- H_0rejection area :
  $D > \chi^2_{(df)}$
- Decision to reject H $_0$:
  D count $> \chi^2_{(df)}$ or $p - value < \alpha$

2.5. Model Interpretation

Model interpretation involves defining how changes in the independent variable affect the dependent variable and understanding the functional relationship between them. To make it easier to interpret the model, odds values are used ratio [11]. The interpretation of the intercept is the probability value when all variables are calculated based on the value π.

2.6. Akaike Information Criterion (AIC)

Tables To choose the best model from the model, it can be seen from the *Akaike value Information Criterion* (AIC). The smaller the AIC value, the better the model. The AIC calculation is formulated as follows [11][14]:

[DOI: 10.14710/JSUNIMUS.12.2.2024.42-53]

$$\text{AIC} = -2 \ln L(\hat{\boldsymbol{\theta}}) + 2p \quad (12)$$

Where :

$L(\hat{\boldsymbol{\theta}})$	:	maximum value of *the likelihood function*
p	:	many parameters in the model

2.7. Human Development Index

The Human Development Index (HDI) is a composite measure that combines three essential dimensions of human development.: life expectancy, education, and a reasonable standard of living.These dimensions have a broad significance, as each one is influenced by numerous contributing factors[12].

The HDI value ranges from 0 to 100 and reflects the level of human development achieved as a result of a country's or region's development efforts. A higher HDI indicates a better overall human development achievement in that country or region [12].

3. METHODOLOGY

3.1. Data and Variabel

The data for this research is secondary data sourced from published reports by the Badan Pusat Statistik (BPS). Specifically, it includes HDI data for Regencies/Cities in Papua and West Papua Provinces from 2019.

The variables observed in this study consist of one dependent variable and four independent variables which are explained in Table 1.

Table 1. Research Variables

Variable	Information
Y*	Human Development Index (HDI)
X_1	Percentage of the Population Living in Poverty
X_2	Open Unemployment Rate (TPT)
X_3	Average Per Capita Expenditure
X_4	School Enrollment Rates

According to the latest grouping from BPS (2015), it can be grouped into four groups as follows

i. 0 = group low if HDI < 60
ii. 1 = medium group If $60 \leq$ HDI < 70
iii. 2 = high group if $70 \leq$ HDI < 80
iv. 3 = group very tall HDI ≥ 80

In this research, if the HDI is divided according to BPS regulations, that is, there is four category, so that There is a number of category Which empty. Regency/city inDistricts/Cities

[DOI: 10.14710/JSUNIMUS.12.2.2024.42-53]

in Papua and West Papua Provinces in 2019 were in the low and middle category upper middle. Thus, in this research, the distribution of HDI is divided become three categories namely:

i. 1 = Low if HDI < 60
ii. 2 = Currently If 60 ≤ HDI < 70
iii. 3 = Tall if HDI ≥ 70

3.2. Analysis Procedur

This The steps taken in this research are as follows:

1. Conduct descriptive analysis to determine the HDI in Papua Province and West Papua Province.
2. Testing multicollinearity between independent variables
3. Conduct ordinal logistic regression model analysis
   a. Create an ordinal logistic regression model
   b. Perform parameter estimation
   c. Perform both simultaneous and partial parameter significance tests to determine if any independent variables have a significant impact on the dependent variable.
   d. Carry out model suitability tests
4. Draw conclusions from observations,

4. RESULTS AND DISCUSSION

4.1. Descriptive Statistics

The data used in this research is HDI data in Papua and West Papua Provinces with the following categorization frequencies:

Table 2. Descriptive Dependent variables

Category	Frequency	Proportion
Low HDI (1)	22	52.38%
Medium HDI (2)	14	33.33%
High HDI (3)	6	14.29%

Table 2 shows that districts/cities in Papua and West Papua Provinces have HDI in the low category of 52.38%, medium category 33.33%and high category of 14.29%.

Table 3. Descriptive Independent variables for Each Category

	IPM					
	Kategori 1		Kategori 2		Kategori 3	
	Mean	Varian	Mean	Varian	Mean	Varian
X_1	34.675	23.251	22.646	61.970	16.861	28.482
X_2	1.562	1.706	5.041	6.686	9.563	3.471
X_3	5.580	0.995	8.004	1.767	12.268	3.759
X_4	55.276	237.091	78.457	51.502	81.587	50.846

Based on Table 3, it is evident that for category 1. Respectively the average percentage of poor people (X_1).,TPT (X_2), per capita expenditure (X_3), and APS $(X_4)$are (34.675),

[DOI: 10.14710/JSUNIMUS.12.2.2024.42-53]

(1.562). (5.580), and (55.276). The averages for category 2 respectively for variables X_1, X_2, X_3, and X_4 are (22.646), (5.041), (8.004), and (51.502). Lastly for category 3. the average values X_1, X_2, X_3, are X_4. (9.563), (12.268), and, (81.587) respectively (16.861).

4.2. Multicollinearity Checks

Evaluating multicollinearity seeks to determine if there are any breaches of the fundamental assumption of multicollinearity, particularly the existence of linear relationships among independent variables in the regression model. To detect signs of multicollinearity, the VIF values are analyzed. A regression model is deemed to have no multicollinearity issues if the VIF values are under 10.

Table 4. Multicollinearity Checking

Variable	*R- Square*	VIF
X_1	0.610	2.564
X_2	0.686	3.185
X_3	0.724	3.623
X_4	0.496	1.984

Given that Table 4 shows VIF values for all independent variables are below 10, it suggests that the assumption of multicollinearity is not violated.

4.3. Simultaneous Test

The simultaneous test produces a calculated 68.460*chi-square value of and chi-square* value table of 52.9485. Because the calculated chi-square value is greater than the table *chi-square* , reject it H_0. This means that with an error rate ($\alpha = 10\%$)there is at least one independent variable that has a significant effect on the dependent variable.

4.4. Partial Parameter Test (Wald Test)

Table 5. Partial Test of Independent variables

Variable	Wald	P- value	Decision
X_1	1,653	0.198	Failed to Reject H_0
X_2	3,478	0.062	Reject H_0
X_3	5,753	0.016	Reject H_0
X_4	2,145	0.143	Failed to Reject H_0

Table 5 Shows that $X_1$and X_4 has *p- value* $> \alpha = 0.10$, then fail to reject H_0. This means that the variables percentage of poor population (X_1) and school enrollment rates (X_4) do not have a significant effect on HDI (Y). Meanwhile, variables $X_3$and X_4have *p- values* $< \alpha = 0{,}10$. This means the variable is average per capita expenditure $(X_3)$and the open unemployment rate (X_2) has a significant effect on HDI (Y) at a significance level. 10%.Then, re-analysis will be carried out on the significant independent variable, namely the average per capita expenditure variable (X_3) and the open unemployment rate (X_2).

4.5. Concurrent Test (After Deletion $\mathbf{X_1, X_4}$)

Simultaneous test after removal X_1, X_4 produces a *chi-square value* calculate by 61.586, and *chi-square value* table is 52.9485 because of the *chi-square value* count is greater

[DOI: 10.14710/JSUNIMUS.12.2.2024.42-53]

than *chi-square* table then reject it H_0. This means that with an error rate ($\alpha = 10\%$)there is at least one independent variable that has a significant effect on the dependent variable.

4.6. Partial Parameter Test (After Deletion X_1, X_4)

Next, a partial test will be carried out using the Wald test after deletion X_1 and X_4. The Wald Test results can be seen in Table 6.

Table 6 Partial Test After Deletion

Variable	Wald	*P- value*
X_2	4.420	0.036
X_3	8.840	0.006

Tables 6 shows for variables $X_3$and X_4 has *a p- value* $< \alpha = 0.10$. This means the variable is average per capita expenditure $(X_3)$and the open unemployment rate (X_2)has a significant effect on HDI (Y) at the significance level 10%.

4.7. Model Determination Coefficient

Coefficient The determinations used in this research can be seen in Table 7.

Table 7 Coefficient of Determination

Pseudo R- Square	
Cox and Snell	0.769
Nagelkerke	0.894
McFadden	0.756

Table 7 displays a McFadden R^2 of 0.746, a Cox and Snell R^2 of 0.769, and a Nagelkerke R^2 of 0.894, or 89.4%. This indicates that the average per capita expenditure and the Open Unemployment Rate together explain 89.4% of the variation in the overall human development index, with the remaining 11.6% attributed to factors not included in the model.

4.8. Model Parameter Estimation

The results of estimating model parameters in this study can be seen in Table 8.

Table 8 Parameter Estimates

Variable	Estimate	df	P- value
$Y_{(1)}$	13.982	1	0.002
$Y_{(2)}$	24.324	1	0.003
X_2	0.994	1	0.036
X_4	1.550	1	0.003

Table 8 shows that the variables X_2 and X_4 have a significant effect on the model with a significance level of 10%. Because the dependent variable consists of three categories, there are two logit models using all independent variables as follows.

[DOI: 10.14710/JSUNIMUS.12.2.2024.42-53]

- First model

$$\hat{\pi}_1 = \frac{\exp(13.982 + 0.994X_1 + 1.550X_2)}{1 + \exp(13.982 + 0.994X_1 + 1.550X_2)}$$

$\hat{\pi}_1 = P(Y = 1) = P(Y \leq 1)$

- Second model

$$\hat{\pi}_2 = \frac{exp(24.324 + 0.994X_1 + 1.550X_2)}{1 + exp(24.324 + 0.994X_1 + 1.550X_2)}$$

$\hat{\pi}_2 = 1 - P(Y \leq 2)$

In the logistic regression model, what is used to interpret the coefficients is the odds ratio . Odds value The ratio is the ratio between the tendency (risk) for an event to occur in the case group and the control group. So the model formed can be interpreted using *odds ratio* . Odds ratio of average per capita expenditure (X_3): $\Psi = e^{1,550} = 4.7$. This means that the average per capita expenditure has a trend of 4.7 times to have a higher HDI compared to other districts or cities, assuming other variables are constant.

4.9. Model Fit Test

The model suitability test is carried out to determine whether there are differences between the observation results and the prediction results after the simultaneous model is formed.

Table 9 Model Fit Test

	Chi Square	Df	P- value
Pearson	33.457	80	1.000
Deviance	20.978	80	1.000

Table 9 show that the Chi Square values are calculated for Pearson and Devience smaller than the value Chi Square table. So it failed to reject H_0. This means that the model formed is appropriate.

4.10. *Akaike Information Criterion* (AIC)

Next, we will check the goodness of fit value of the model on the variable open unemployment rate $(X_2)$and average per capita expenditure (X_3)using *Akaike Information Criterion* (AIC). After checking, the AIC value obtained was 28.978

5. CONCLUSION

Based on the research results, it was found that the results of simultaneous testing had a significant effect on the Human Development Index using ordinal logistic regression, namely the Open Unemployment Rate and Average Per Capita Expenditure at a significance level of 10%. The coefficient of determination of the variables Open Unemployment Rate and Average Per Capita Expenditure is 89.4%. Then, after testing the suitability of the model using *Goodness of fit,* it was concluded that the model formed was in accordance with the AIC value of 28.978. This shows that the Open Unemployment Rate and Average Per Capita Expenditure

[DOI: 10.14710/JSUNIMUS.12.2.2024.42-53]

variables influence the Human Development Index in Papua and West Papua Provinces in 2019.

ACKNOWLEDGMENT

The author would like to express his deepest gratitude to the Central Statistics Agency (BPS) of Papua Province and West Papua Province for providing secondary data used in this study. Thanks, are also extended to all parties who have helped, support, and guidance during the research process. Support from family, friends, and colleagues is also greatly appreciated in completing this research.

REFERENCES

[1] Ayu. LD, Putri. EM, and Indrasetianingsih. A. “Modeling the Human Development Index and Gender Development Index in Indonesia using the Probit Regression Approach Bivariate” . Journal of Mathematics, Statistics and Computing, 1-4. 2020.

[2] Sari. M, and Purhadi. “Pemodelan Indeks Pembangunan Manusia Provinsi Jawa Barat, Jawa Timur Dan Jawa Tengah Tahun 2019 Dengan Menggunakan Metode Regresi Logistik Ordinal”, Jurnal Gaussian, 10 (1). 2021.

[3] Nefri. N, and Pramesti. W. “Pemodelan Regresi Logistik Ordinal Terhadap Indeks Pembangunan Manusia (IPM) Di Jawa Tengah Tahun 2021”. Prosiding Seminar Nasional Hasil Riset dan Pengabdian, E-ISSN: 2776-5105. 2021.

[4] Christyadi. S, Satriya. A, and Goejantoro. R. “ Pemodelan Indeks Pembangunan Manusia (IPM) Menggunakan Analisis Regresi Probit (Studi Kasus: Indeks Pembangunan Manusia (IPM) di Pulau Kalimantan Tahun 2017)”, Jurnal EKSPONENSIAL Volume 11(2), Nopember 2020.

[5] Agresti, A, Categorical Data Analysis (2nd ed). New Jersey: John Wiley & Sons, Inc. 2002.

[6] Budyanra. B, and Azzahra. GN, “Penerapan Regresi Logistik Ordinal Proportional Odds Model pada Analisis Faktor-Faktor yang Mempengaruhi Kelengkapan Imunisasi Dasar Anak Balita di Provinsi Aceh Tahun 2015”, MEDIA STATISTIKA 10(1) :37-47. 2017.

[7] Fauzan. A, Rahmah. AH, and Pradana. SC, “Model Regresi Logistik Ordinal untuk Menentukan Faktor Pengambilan Keputusan Calon Mahasiswa Memilih Program Studi Statistika”, Statistika, Vol. 18 No. 1, 85 – 96. 2018

[8] Akbar, SJ, A. Mukarromah and L. Paramita. “Ordinal Logistic Regression Bagging on the Nutritional Status of Toddlers”. *Statistical Media,* 3(2): 103-116. 2010

[9] Agresti, A. Analysis of Ordinal Categorical Data (2nd ed). New Jersey: John Wiley & Sons, Inc. 2010

[10] Hosmer , D.W. & Lemeshow . *Applied Logistics Regression* . New York : John Wiley and Sons , Inc. 2000

[DOI: 10.14710/JSUNIMUS.12.2.2024.42-53]

[11] Hosmer , D.W., Lemeshow , S., & Sturdivant . *Applied Logistics Regression (3rd ed)* . New York : John Wiley & Sons , Inc. 2013.

[12] BPS. Human Development Index 2015. Jakarta: Central Statistics Agency. 2015.

[13] Hocking. R. R, *Method and Applications of Linear Models* (2^{nd} Edition ed), New York: John Wiley and Sons, Inc, 1996.

[14] Bozdogan. H. Akaike's information criterion and recent developments in information complexity. *Journal of Mathematical Psychology. 44*(1). 62–91. https://doi.org/10.1006/jmps.1999.1277. 2000

[15] Gujarati. D. N. & Porter. D. C. *Basic Econometrics*. 5^{th} edition. McGrawHill. New York. 2009.

[DOI: 10.14710/JSUNIMUS.12.2.2024.42-53]