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THE PERFORMANCE OF POLYNOMIAL ORDINAL LOGISTIC REGRESSION ANALYSIS ON HYPERTENSION RISK MODELING

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Abstract: Hypertension prevalence in Indonesia is on the rise. The risk of hypertension exhibits a non-linear relationship with predictors such as age, where the risk increases with age but declines in older individuals. This study aimed to analyze the factors influencing hypertension risk using polynomial ordinal logistic regression analysis. Cholesterol levels and mean arterial pressure were identified as significant linear predictors of hypertension risk. Additionally, age showed a significant polynomial effect, achieving a classification accuracy of 76.7%. The polynomial ordinal logistic regression model demonstrated improved classification accuracy compared to the linear model, increasing from 67.8% to 76.7%. These findings highlight the importance of incorporating non-linear relationships in predictive models to enhance the accuracy of hypertension risk assessment.

Keywords: Hypertension, Ordinal Logistic Regression, Polynomial.

2020 AMS Subject Classification: 62P10.

1. INTRODUCTION

Hypertension is characterized by systolic blood pressure equal to or exceeding 140 mmHg or diastolic blood pressure equal to or exceeding 90 mmHg [1]. Known as "The Silent Killer," hypertension often strikes without warning, presenting no symptoms or signs. It is a major

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contributor to various cardiovascular diseases, including stroke and heart disease, which remain significant global health issues. According to the World Health Organization (WHO), over 1.13 billion people globally suffer from hypertension, with the majority (two-thirds) residing in developing countries. In Indonesia, hypertension is a major health issue. Data indicates that the prevalence of hypertension in Indonesia is steadily rising. According to the [2] revealed that the prevalence of hypertension among adults in Indonesia reached 34.1%, an increase from 25.8% in 2013. This figure puts Indonesia in a fairly high ranking globally in terms of hypertension prevalence. In addition to its high prevalence, hypertension is also the leading cause of morbidity and mortality in Indonesia. Given its huge impact on public health and health systems, research on hypertension is essential to understand more deeply about risk factors, prevalence, effective prevention and treatment strategies.

Various previous studies have discussed the factors that affect the incidence of hypertension. For example, a study by [3] using the Cox proportional hazards regression method found that waist circumference had a more significant influence on the incidence of hypertension compared to body mass index (BMI). On the other hand, the study of [4], which also used the Cox proportional hazards regression method, revealed that changes in BMI have a significant impact on the short-term incidence of hypertension. Research by [5] using the binary logistic regression method shows that gender, age, physical activity, and obesity are factors that affect the incidence of hypertension. Meanwhile, [6] used the chi-square test and found a relationship between smoking habits and hypertension in urban areas. Research by [7], using the Cochran's Q test indicated that factors such as gender, ethnicity, education and socioeconomic status, body mass index, waist circumference, smoking, and dyslipidemia significantly contribute to hypertension. Research by [8] used ordinal logistic regression and found that the variable of total cholesterol levels was related to the incidence of hypertension. A study conducted by [9] using ordinal logistic regression analysis with maximum likelihood estimation (MLE) and the Bayesian method showed that age and nutritional status had an impact on the prevalence of hypertension in Bali Province.

Research by [10] concluded that there is a nonlinear relationship between systolic blood pressure (SBP) levels in the normal range and hypertension in older adults. This means that it does not mean that the older a person is, the higher the risk of hypertension. It is also in line with research that has been conducted by [11] which shows that the risk of hypertension increases with age, especially in the age group of 50-60 years. However, at the age of over 80, the increased risk of hypertension becomes more flat, possibly due to natural selection factors and physiological changes in the aging body. This confirms that the relationship between age and hypertension risk is not linear. This can also apply to other variables such as physical activity. Research conducted by [12] found that moderate physical activity may reduce the risk of hypertension, but too little or too much physical activity may increase the risk, suggesting a pattern of relationships that are not always linear. Therefore, several studies on hypertension modeling were conducted using a nonparametric logistic regression approach [13-15]. However, in this study we used a polynomial logistic regression approach. This study aims to model the risk of hypertension using a polynomial ordinal logistic regression approach. This method is intended to capture more complex relationships between predictor variables and the response variable, with the goal of enhancing the accuracy of predictions and improving the understanding of the risk factors associated with hypertension.

2. PRELIMINARIES

This section presents the study dataset's description and the introduction of the orde polynomial from parametric ordinal logistic regression models.

2.1. Dataset

This study used primary data. According to [16], the Slovin formula is a formula used to find a sample size that is considered representative of the entire population. Therefore, the Slovin formula was used to determine the sample size with an error rate of 10%, it was determined that the required number of samples was about 90. The variables utilized in this study are delineated in the following table.

TABLE 1. Research Variables

Variable	Variable Name	Information	Scale
Y	Hypertension Rate	1= Normal 2= Pre-hypertension 3=Hypertension	Ordinal
X_1	Age	Year	Ratio
X_2	Body Mass Index	$\frac{kg}{m^2}$	Ratio
X_3	Cholesterol	$\frac{mg}{dL}$	Ratio
X_4	Mean Average Pressure	$mmHg$	Ratio
X_5	Physical Activity	0=Yes 1=No	Nominal
X_6	History of Diabetes	0=Yes 1=No	Nominal
X_7	History of Hypertension	0=Yes 1=No	Nominal
X_8	Smoking Status	0=Yes 1=No	Nominal

The flow of this research is as follows:

1. Describe the hypertension level response variables consisting of three categories.
2. Describe the predictor variables that are suspected to affect the level of hypertension.
3. Estimating the parameters of the ordinal logistic regression model individually using the linear method.
4. Estimate the significant variables ordinal logistic regression model parameters and compute the deviation and accuracy of its classification.
5. Estimating the parameters of the ordinal logistic regression model univariably using the polynomial method.
6. Estimating the parameters of the ordinal logistic regression model using linear and polynomial methods for significant variables, and assessing the deviation and accuracy of its classification.
7. Compare the accuracy of the classification between the linear method and the polynomial method to choose the best one. The criteria for selecting the best model are based on the smallest deviation value and the largest classification accuracy value.

2.2. Polynomial Ordinal Logistic Regression Model

Ordinal logistic regression is a statistical method used to examine the relationship between a response variable that has three or more ordinal categories and one or more predictor variables. The model employed in ordinal logistic regression is the cumulative logit model.

If there is a random sample of the shared distribution (Y,X) where Y is an ordinal response with q category and $X=(X_1,X_2,\dots,X_t)$ is the vector of the predictor variable, then the ordinal logistic regression model is stated as follows:

(1) $$g\left(\gamma_j(X)\right)=\theta_j+\sum_{k=1}^{t}\beta_k X_k \text{ , Where } j=1,2,\dots,q-1.$$

where θ_j is the intercept parameter, $\beta_1,\beta_2,\dots,\beta_t$ adalah the regression coefficient parameter and $\gamma_j(X)=P(Y\le j|X)$ is the cumulative chance of the j-th category response variable while $g\left(\gamma_j(X)\right)$ is the link function. According to [17], the function of a link logit is defined as follows:

(2) $$g\left(\gamma_j(X)\right)=ln\left(\frac{\gamma_j(X)}{1-\gamma_j(X)}\right)$$

From equations (1) and (2), the ordinal logistic regression model is obtained as follows:

(3) $$ln\left(\frac{\gamma_j(X)}{1-\gamma_j(X)}\right)=\theta_j+\sum_{k=1}^{t}\beta_k X_k$$

Polynomial Ordinal Logistic Regression is a development of ordinal logistic regression where the relationship between the predictor variable and its logit link has a polynomial relationship [18,19]. Thus, the polynomial ordinal logistics regression model is expressed as follows:

(4) $$ln\left(\frac{\gamma_j(X)}{1-\gamma_j(X)}\right) = \theta_j + \sum_{k=1}^{t} \beta_k X_{k(r_k)}$$

where $\boldsymbol{x}_{k(r_k)} = \begin{bmatrix} x_k & x_k^2 & \dots & x_k^{r_k} \end{bmatrix}^T$ and r_k are the polynomial degrees of the k-th predictor variable. Based on equation (4), the cumulative odds $\gamma_j(X) = P(Y \leq j|X)$ are obtained as follows:

(5) $$\gamma_j(X) = P(Y \leq j|X) = \frac{\exp\left(\theta_j+\sum_{k=1}^{t} \beta_k X_{k(r_k)}\right)}{1+\exp\left(\theta_j+\sum_{k=1}^{t} \beta_k X_{k(r_k)}\right)}$$

If $\pi_j(X) = P(Y = j|X)$ is the chance of the value $Y = j$ if X is known for $j = 1,2, \dots, q$ then the relationship between the opportunity vector $\pi = (\pi_1(X), \pi_2(X), \dots, \pi_q(X))$ and the ordinal-scale Y response variable can be expressed in $\gamma_j(X) = \sum_{s=1}^{j} \pi_s(X)$, $j = 1,2, \dots, q-1$.

Thus, the relationship between $\pi_s(X)$ and $\gamma_j(X)$ is:

(6) $$\gamma_1(X) = \pi_1(X)$$

(7) $$\gamma_2(X) = \pi_1(X) + \pi_2(X)$$

(8) $$\gamma_q(X) = \pi_1(X) + \pi_2(X) + \cdots + \pi_q(X)$$

Suppose the number of response variable categories is 3, then the odds obtained from each response category are as follows:

(9) $$\pi_1(X) = \frac{\exp\left(\theta_1+\sum_{k=1}^{t} \beta_k X_{k(r_k)}\right)}{1+\exp\left(\theta_1+\sum_{k=1}^{t} \beta_k X_{k(r_k)}\right)}$$

(10) $$\pi_2(X) = \frac{\exp\left(\theta_2+\sum_{k=1}^{t} \beta_k X_{k(r_k)}\right)}{1+\exp\left(\theta_2+\sum_{k=1}^{t} \beta_k X_{k(r_k)}\right)} - \frac{\exp\left(\theta_1+\sum_{k=1}^{t} \beta_k X_{k(r_k)}\right)}{1+\exp\left(\theta_1+\sum_{k=1}^{t} \beta_k X_{k(r_k)}\right)}$$

(11) $$\pi_3(X) = 1 - \frac{\exp\left(\theta_2+\sum_{k=1}^{t} \beta_k X_{k(r_k)}\right)}{1+\exp\left(\theta_2+\sum_{k=1}^{t} \beta_k X_{k(r_k)}\right)} = \frac{1}{1+\exp\left(\theta_2+\sum_{k=1}^{t} \beta_k X_{k(r_k)}\right)}$$

3. MAIN RESULTS

In this section, we present the results of this study including characteristic of research variables, modeling the risk of hypertension based on linear ordinal logistic regression, modeling the risk of hypertension based on polynomial ordinal logistic regression and determination of the best model.

3.1. Characteristics of Research Variables

The characteristic of response variable described through the following Table 2.

TABLE 2. Description of response variables

Category	Amount	Percentage
1	29	32.22%
2	34	37.78%
3	27	30.00%
Total	90	100.00%

The results of the description in Table 2 can be visualized in the form of a diagram in Figure 1 below.

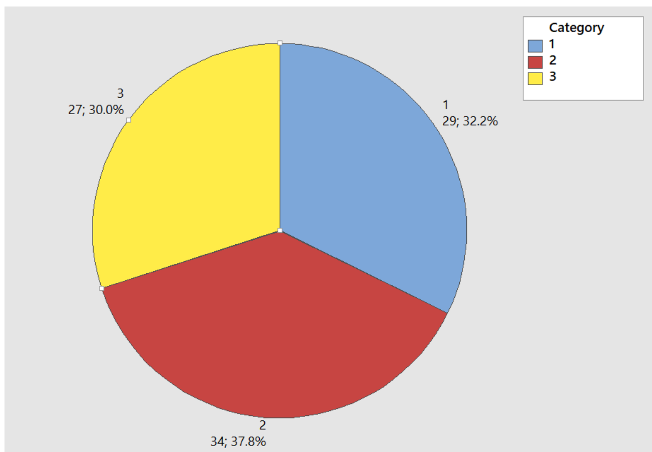

Figure 1. Visualization of response variable descriptions

After visualizing the description of the response variables, we present a description of the continuous predictor variables that include age, body mass index, cholesterol and mean average pressure in the following Table 3.

TABLE 3. Description of continuous predictor variables

Variable	Mean	StDev	Minimum	Median	Maximum
X_1	61.589	8.930	41.000	62.500	79.000
X_2	26.201	4.162	17.715	25.928	36.444
X_3	131.60	32.47	64.00	130.50	231.00
X_4	99.54	12.04	70.33	99.33	133

Discrete predictor variables that include physical activity, history of diabetes, history of hypertension and smoking are depicted in the contingency table in Table 4 below.

TABLE 4. Description of discrete predictor variables

Hypertension Rate	Normal	Pre- Hypertension	Hypertension
Physical Activity			
Yes	16	23	16
No	13	11	11
History of Diabetes			
Yes	17	14	13
No	12	20	14
History of Hypertension			
Yes	10	13	12
No	19	21	15
Smoking Status			
Yes	10	6	9
No	19	28	18

3.2. Modeling the Risk of Hypertension based on Linear Ordinal Logistic Regression

The parameters of the ordinal logistic regression model will be estimated univariably first by regressing each predictor variable to the response variable. The results of the univariable estimation of ordinal logistic regression model parameters are presented in the following Table 5.

TABLE 5. Results of parameter estimation of univariable ordinal logistic regression model

Predictor	Coef	SE Coef	Z	P
X_1	0.0009266	0.0218462	0.04	0.966
X_2	-0.0474221	0.0472372	-1.00	0.315
X_3	-0.0183378	0.0064887	-2.83	0.005*
X_4	-0.165108	0.0276229	-5.98	0.000*
X_5	0.1398530	0.3982930	0.35	0.725
X_6	-0.3201160	0.3895070	-0.82	0.411
X_7	0.3039920	0.3991300	0.76	0.446
X_8	-0.0691442	0.4332790	-0.16	0.873

* Significance to $\alpha = 10\%$

Based on Table 5, the significant predictor variables with a significance of $\alpha = 10\%$ are the X_3 and X_4 variables. The following are the results of estimating the parameters of the univariable ordinal logistic regression model using significant variables to the response variables listed in Table 6.

TABLE 6. Parameter estimation of significant variable based on ordinal logistic regression

Predictor	Coef	SE Coef	Z	P
Const(1)	20.4015	3.51829	5.8	0.000
Const(2)	23.2954	3.78617	6.15	0.000
X_3	-0.0272326	0.0086199	-3.16	0.002
X_4	-0.182678	0.0310396	-5.89	0.000

Log-Likelihood = -64.562

Deviance = 129.124, df = 176, p-value = 0.997

Classification accuracy = 67.8%

3.3. Modeling the Risk of Hypertension based on Polynomial Ordinal Logistic Regression

After the analysis uses linear ordinal logistic regression, it is followed by the analysis of polynomial ordinal logistic regression by adding the quadratic yield variable as the predictor in the regression model. The use of polynomial ordinal logistic regression analysis aims to determine the existence of a polynomial relationship with degree 2 or quadratic between the predictor variable and the response variable. The results of the parameter estimation of the univariable polynomial ordinal ordinal logistic regression model are shown in Table 7 as follows.

TABLE 7. Parameter estimation results of univariable polynomial ordinal logistic regression

Predictor	Coef	SE Coef	Z	P
X_1	0.440129	0.258555	1.7	0.089*
${X_1}^2$	-0.0036271	0.0021224	-1.71	0.087*
X_2	0.289213	0.483367	0.6	0.55
${X_2}^2$	-0.0062969	0.0090206	-0.7	0.485
X_3	-0.0422869	0.038821	-1.09	0.276
${X_3}^2$	0.0000877	0.0001394	0.63	0.529
X_4	-0.0845391	0.396017	-0.21	0.831
${X_4}^2$	-0.0004048	0.0019883	-0.2	0.839

* Significance to $\alpha = 10\%$

Based on Table 7. It can be seen that the significant variables with $\alpha = 10\%$ are variables X_1 and ${X_1}^2$. In Table 5, the previous variable X_1 was not significant using linear ordinal logistic regression, but it turned out to be significant using polynomial ordinal logistic regression. This shows that the relationship between the X_1 predictor variable and the response variable tends to be polynomial.

Furthermore, a multivariable polynomial ordinal logistic regression analysis was carried out by listing linear and polynomial significant variables. The following are the results of estimation of multivariable polynomial ordinal logistic regression parameters in Table 8.

TABLE 8. Parameter estimation results of multivariable polynomial ordinal logistic regression

Predictor	Coef	SE Coef	Z	P
Const(1)	-9.40957	8.02989	-1.17	0.241
Const(2)	-7.6778400	8.00806	-0.96	0.338
X_1	0.28912800	0.310383	0.93	0.352
${X_1}^2$	-0.0030524	0.0025781	-1.18	0.236
X_3	-0.0291096	0.0089861	-3.24	0.001
X_4	-0.216465	0.0360278	-6.01	0.000

Log-Likelihood = -60.150

Deviance = 120.301, df = 174, p-value = 0.999

Classification accuracy = 76.7%

3.4. Determination of the Best Model

In summary, the comparison of the classification accuracy value of modeling the risk of hypertension based on the methods used is presented in Table 9 below:

TABLE 9. The comparison of classification accuracy

Methods	Classification Accuracy
Linear ordinal logistic regression	67.8%
Polynomial ordinal logistic regression	76.7%

As illustrated in Table 9, there is a notable improvement in model classification accuracy, increasing from 67.8% to 76.7%. This indicates that the relationship between the predictor variable and the response variable may be non-linear, as demonstrated by the polynomial nature of the X_1 variable.

With three response variable categories, two polynomial ordinal logistic regression equations are formulated as follows:

$$\pi_1(X) = \frac{\exp\left(-9{,}40957 + 0.28912800X_{1(1)} - 0.0030524X_{1(2)} - 0.0291096X^*_{3(1)} - 0.216465X^*_{4(1)}\right)}{1 + \exp\left(-9{,}40957 + 0.28912800X_{1(1)} - 0.0030524X_{1(2)} - 0.0291096X^*_{3(1)} - 0.216465X^*_{4(1)}\right)}$$

$$\pi_2(X) = \frac{\exp\left(-7.6778400 + 0.28912800X_{1(1)} - 0.0030524X_{1(2)} - 0.0291096X^*_{3(1)} - 0.216465X^*_{4(1)}\right)}{1 + \exp\left(-7.6778400 + 0.28912800X_{1(1)} - 0.0030524X_{1(2)} - 0.0291096X^*_{3(1)} - 0.216465X_{4(1)}\right)} - \frac{\exp\left(-9{,}40957 + 0.28912800X_{1(1)} - 0.0030524X_{1(2)} - 0.0291096X^*_{3(1)} - 0.216465X^*_{4(1)}\right)}{1 + \exp\left(-9{,}40957 + 0.28912800X_{1(1)} - 0.0030524X_{1(2)} - 0.0291096X^*_{3(1)} - 0.216465X^*_{4(1)}\right)}$$

With the above equation, the odds ratio value of each parameter is obtained in the following Table 10.

TABLE 10. Odds Ratio Parameters

Variable	Coef	Odds Ratio
X_1	0.28912800	1.34
${X_1}^2$	-0.0030524	1.00
X_3	-0.0291096	0.97
X_4	-0.216465	0.81

In Table 10 based on the odd ratio value, it can be seen that every 1 unit increase in age will significantly increase the risk of hypertension by 1.34 times, whereas every increase in cholesterol by 1 unit will significantly reduce the risk of hypertension by 0.97 times and every increase in Mean Average Pressure by 1 unit will significantly reduce the risk of hypertension by 0.81 times.

4. CONCLUSIONS

The results of the analysis indicate that the significant predictor variables that affect the risk of hypertension linearly are the cholesterol (X_3) and the mean average pressure (X_4). While the significant predictor variable that affects the risk of hypertension with a polynomial (quadratic) effect is the age (X_1). This shows that the age which was previously insignificant in the linear ordinal logistic regression model turned out to be significant in the polynomial ordinal logistic regression model which resulted in better classification accuracy of 76.7%. This means that the relationship between the age and the risk of hypertension is not linear, but there is a polynomial tendency.

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CONFLICT OF INTERESTS

The authors state that they have no conflicts of interest.

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