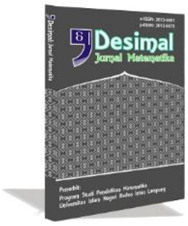
Contents lists available at DJM
DESIMAL: JURNAL MATEMATIKA
p-ISSN: 2613-9073 (print), e-ISSN: 2613-9081 (online), DOI 10.24042/djm
http://ejournal.radenintan.ac.id/index.php/desimal/index



Ordinal logistic regression model on the level of job relevance of graduates

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ARTICLE INFO

Article History
Received : *26-10-2023*
Revised : *26-11-2023*
Accepted : *22-12-2023*
Published : *30-12-2023*

Keywords:
Job Relevance of Graduates; Missing Data; Ordinal Logistic Regression; Proportion Odds Model; Single Imputation.

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Doi: 10.24042/djm.v6i3.19716

ABSTRACT

The ordinal logistic regression model is one of the statistical models used to classify ordinal data. The purpose of this study is to identify the relevance of FKIP Muhammadiyah Pringsewu University Lampung graduates. The population in this study were FKIP Muhammadiyah Pringsewu University Lampung graduates in three academic years from 2018-2021. The total of the sample in this study was 133 graduates. There was missing data that was classified as Missing Random (MAR). The ordinal logistic regression model used an odds proportion model. This study will analyze the relationship between the response variable is the relevance of the graduate's work according to the field of work that has three classifications high, medium, and low, against the nine predictor variables predicted affecting the predictor variable. The result of the data description available stated that 80.3% of graduates had a high level of job relevance, 11.4% of graduates had a moderate level of job, and 8.3% of graduates had a low level of job relevance. Then the result of the ordinal logistic regression model using the proportional odds model showed that the variable predictor IPK graduates with categories 3.01-3.50; 3.406; and 3.51-4.00, predictor variable of looking for or getting a job either before or after, and variables predictor types of permanent jobs give a significant influence on the level of job relevance of graduates.

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INTRODUCTION

Ordinal logistic regression is a regression analysis that is used to analyze the relationship between response variables and explanatory variables that vary across categories, where they are polychotomous with an ordinal scale, and independent variables can be categorical, interval, or ratio scale variables (Hosmer & Lemeshow, 2000; Liu & Koirala, 2012). The ordinal logistic regression model is more appropriate when the dependent variable used has ordinal categories (Jamaludin et al., 2020). Ordinal models are more efficient when efficiency is measured by considering the asymptotic rate of excess error due to parameter estimates (Campbell & Donner, 1989). The ordinal logit model is more suitable for use in data that takes goodness of fit into account (Ari & Yildiz, 2014). The proportional odds model can evaluate the model's skill in dealing with complex data (Brant, 1990).

Missing data is a problem that can be found in data collection (Donders et al., 2006). A quick approach that can be used for missing data is to replace it with the mean, median, or mode value (Zhang, 2016). One method that can be used is single imputation. Single imputation is filling in a value for missing data (Plaia & Bondì, 2006). If data is missing, classified as missing at random (MAR), there are several methods that can be used, namely the Rasch model method (RAS-R), no imputation (NOIMP), or listwise deletion (LD) (Hardouin et al., 2011).

The use of statistical analysis using ordinal logistic regression can be applied to classifying the relevance of graduate work. As is known, the topic of relevance of graduate work is something that is very important for a university to know about its achievements so that it does not become something unfamiliar. This is in line with the hope that a university is seen as an institution that is expected to produce quality human resources (Setyaningsih, 2013). This means that it is a challenge in itself for universities so that the graduates they produce fall into a quality category that can match the profile of graduates of each study program and can be used in the world of work, so that the role of the college knowledge obtained can be applied in work (Saputra, 2014).

Quality college graduates are an achievement that study programs want to achieve (Muhson et al., 2012). The existence and activities of graduates will always be overshadowed by the quality of higher education. Graduates who are well absorbed by the job market, whether they act as entrepreneurs or work with other people, become an assessment of whether the existence of the institution (department or faculty) will be maintained or not. In this case, the professional absorption of graduates in accordance with society's needs is reflected in the need for work qualifications that are tailored to graduates' undergraduate studies (Rachman et al., 2018). The study of the relevance of graduates to their field of work is an interesting topic to discuss because quality graduates are the graduates that users are looking for, so universities are expected to be able to know what factors support the relevance of graduates to their field of work.

Based on the study of previous research results and the description above, the aim of this research is to build an ordinal logistic regression analysis model to identify variables that influence the job relevance of graduates of the Faculty of Teacher Training and Education (FKIP) Muhammadiyah University of Pringsewu (UMPRI) Lampung.

METHOD

Single Imputation

The method used to overcome the problem of missing data includes single imputation. One of the treatments using the single imputation method is using the mode value. The use of the mode value is used to handle missing data in data with categorical variables (Zhang, 2016).

Multicollinearity Test

The multicollinearity test is a test to determine whether there is a linear relationship or correlation between significant predictor variables in the regression model. In ordinal logistic regression analysis, cases of multicollinearity are not permitted. Techniques that can be used to detect multicollinearity include obtaining Variance Inflation Factor (VIF) values. To detect multicollinearity, you can use VIF, which is expressed as follows:

$$VIF_i = \frac{1}{1-R_i^2} \quad (1)$$

where R_i^2 is the coefficient of determination.

Ordinal Logistic Regression

Ordinal logistic regression is a statistical method for analyzing response variables with an ordinal scale of three or more categories (Siahaan et al., 2017). Ordinal logistic regression analysis aims to find an equation that expresses the probability (π_r) for each category, $r = 1,2,3,\cdots,k$, with the property $\pi_1 + \pi_2 + \cdots + \pi_k = 1$, where k is the number of categories in the variable response (Emptage & Dobson, 1992). The model that can be used for ordinal logistic regression is the logit model, which is expressed in cumulative odds. Cumulative logit models can be compared with cumulative odds, namely that the odds are less than or equal to the r-th response category on p predictor variables expressed in vectors x_i is $P(Y \le r|x_i)$, with a greater probability than the r-th response category in the predictor variable $P(Y > r|x_i)$ (Hosmer & Lemeshow, 2000). Cumulative probability $P(Y \le r|x_i)$, as follows:

$$P(Y \le r|x_i) = \pi(x) = \frac{exp(\theta_r + \sum_{m=1}^{p} \beta_m x_{im})}{1+exp(\theta_r + \sum_{m=1}^{p} \beta_m x_{im})} \quad (2)$$

where $x_{im} = (x_{i1}, x_{i2}, \cdots, x_{ip})$ is the i-th observation value $(i = 1,2,\cdots,n)$ of each predictor variable p.

Parameter Estimation

Parameter estimation can be used using the maximum likelihood method. This method obtains the maximum likelihood estimate for β, with the initial step being to form a likelihood function (Siahaan et al., 2017). The method that can be used to estimate logistic model parameters is Maximum Likelihood Estimation (MLE). This method provides an estimate of the β parameter by maximizing the likelihood function. If the probability distribution function for Y_i is $f(Y_i) = \gamma^{Y_i}(1-\gamma)^{1-Y_i}$, then the likelihood function for n independent observations is:

$$L(\beta_0, \beta_1, \beta_2, \cdots, \beta_m) = \prod_{i=1}^{n} \{[\gamma(x_i)]^{Y_i}[1 - \gamma(x_i)]^{1-Y_i}\}$$

$$= \left\{ \left[\frac{\gamma(x_i)}{1-\gamma(x_i)}\right]^{\sum_{i=1}^{n} Y_i} [1-\gamma(x_i)] \right\} \quad (3)$$

Based on the likelihood function, the ln likelihood function is obtained as follows:

$$ln(L(\beta_0, \beta_1, \beta_2, \cdots, \beta_m)) = l(\beta_0, \beta_1, \beta_2, \cdots, \beta_m) = \sum_{i=1}^{n} \left\{ \begin{matrix} Y_i(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k) + \\ [ln1 + e^{(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k)}] \end{matrix} \right\}$$
(4)

Logistic regression parameter estimates are obtained from the first partial derivative of the ln likelihood function for the estimated parameters and then equalized to zero. Estimates of ordinal logistic regression parameters are obtained by reducing the log-likelihood function for the parameters to be estimated and equalizing them to zero. The equation $\frac{\partial L(\beta)}{\partial \beta_m} = 0$ is used to estimate the parameter β_m where $m = 1,2,\cdots,p$, and $\frac{\partial L(\beta)}{\partial \beta_0} = 0$ is an estimate of the intercept β_0 where $r = 1,2,\cdots,r-1$. The resulting equations $\frac{\partial L(\beta)}{\partial \beta_m} = 0$ and $\frac{\partial L(\beta)}{\partial \beta_0} = 0$ are nonlinear functions, so an iteration method is needed to obtain parameter estimates. The iteration method that can be used is Iterative Weighted Least Square (IWLS), namely the Newton-Raphson algorithm (Agresti, 2006).

Simultaneous Test

Simultaneous tests are carried out using the G2 test, or Likelihood Ratio Test, which basically shows whether all the independent variables included in the model have a joint influence on the predictor variables. The hypothesis used is as follows:

Hypothesis:

$H_0: \beta_1 = \beta_2 = \cdots = \beta_p = 0$

(Simultaneously, the predictor variable has no effect on the response variable)

$H_1: \beta_m \neq 0;\ \ m = 1,2,\cdots,p$ (There is at least one of the predictor variables that influences the response variable)

The level of significance used is $\alpha = 0.05$

Test statistics:

$$G^2 = -2\frac{\left(\frac{n_1}{n}\right)^{n_0}}{\prod_{\pi_r}^{Y_i}(1-\pi)^{1-Y_i}} = -2ln\frac{L_0}{L_m} \tag{5}$$

Decision rule:

The G^2 test statistic follows a chi-squared distribution with degrees of freedom for the number of parameters in the model; therefore, to obtain a test decision, one must compare the G^2 value with the following:

H_0 accepted: if $G^2 \leq \chi^2_{(p,\alpha)}$ or $p - value \geq \alpha$

H_0 rejected: if $G^2 > \chi^2_{(p,\alpha)}$ or $p - value < \alpha$

Individual Test

To test the significance of individual model parameters, they can be tested using the Wald test. The results of the Wald test will show whether a predictor variable is significant or worthy of being included in the model or not.

Hypothesis:

$H_0: \beta_m = 0, i = 1,2,\cdots,p$ (There is no influence of the m-th predictor variable on the response variable)

$H_1: \beta_m \neq 0, i = 1,2,\cdots,p$ (there is an influence of the m-th predictor variable on the response variable)

Test statistics:

$$W = \frac{\hat{\beta}_m}{SE(\hat{\beta}_m)} \tag{6}$$

where:

$SE(\hat{\beta}_m) = \sqrt{var\hat{\beta}_m}$

W = Wald test statistical value

$\hat{\beta}_m$ = m-th parameter coefficient estimation

Critical area:

If $|W|$ greater than $Z\alpha_{/2}$ or $p - value$ less than α, then H_0 is rejected. This is because the Wald test follows a normal distribution (Hosmer & Lemeshow, 2000).

Interpretation of Ordinal Logistic Regression Model Coefficients

The interpretation or assessment of the difference/odds ratio ψ is to explain the number of multiples of an increase or decrease in the odds of $Y = 1$ if the value of the predictor variable (X) changes by a certain value (Siahaan et al., 2017). The odds ratio value is always positive. The estimator for the odds ratio is as follows:

$$\psi = exp(\hat{\beta}_m) \tag{7}$$

Data Instruments

The data used in this research is primary data aimed at FKIP UMPRI graduates for the 2018–2019 academic year, 2019–2020 academic year, and 2020–2021 academic year, totaling 445 graduates. The results of filling out the graduate relevance instrument received feedback from 133 graduates.

Job Relevance of Graduates According to Field of Work

The response variable from this research is the relevance of graduate work according to work fields with high, medium, and low classifications. The determination of this classification is based on identifying the type of work according to the profile of graduates in each study program.

Predictor Variables

The predictor variables used in this research are:

(1) Gender (X_1)
1 = male
2 = female

(2) Scientific fields according to the study program (X_2)
1= Guidance and Counseling
2= Mathematics Education
3= Indonesian Language and Literature Education
4= English Language Education
5= Primary Teacher Education

(3) Study period (X_3)
1 = 4 years
2 = 5 years
3 = 6 years
4 = 7 years

(4) Graduate waiting time (X_4)
1 = < 6 month
2 = 6 – 18 months
3 = > 18 months

(5) GPA of graduates (X_5)
1 = < 2,75
2 = 2,76 – 3,00
3 = 3,01 – 3,50
4 = 3,51 – 4,00

(6) Achievements while a student (X_6)
1 = have
2 = not have

(7) Graduation on time (X_7)
1 = yes
2 = no

(8) Looking for/getting a job (X_8)
1 = before
2 = after

(9) Type of job (X_9)
1 = temporary
2 = permanent

Analysis Stages

(1) handling or estimating missing values with single imputation using mode value acquisition
(2) multicollinearity assumption test
(3) ordinal logistic regression analysis

In ordinal logistic regression analysis, several stages are carried out, namely:

a. Simultaneous testing, carrying out tests to determine whether there is an influence between the response variable and the predictor variable simultaneously
b. Individual testing: carrying out individual testing to determine whether there is an influence between the response variable and the predictor variable
c. Selection of the best ordinal logistic regression model
d. Interpretation of the best ordinal logistic regression model

RESULTS AND DISCUSSION

The results of the data description in the job relevance fields recorded on 133 graduates stated that 80.3% of graduates had a high level of job relevance, which means that the type of graduate work is in accordance with the graduate's main profile, namely as an educator; 11.4% of graduates have a medium level of job relevance, which means that the type of graduate work is in accordance with the graduate's profile as an entrepreneur (edupreneurship); and 8.3% of graduates have a low level of job relevance, meaning that the type of work graduates are currently pursuing is outside the graduate profile of teacher and education graduates.

Results of handling missing values with single imputation

In the data that will be analyzed to find out the nine predictor variables that influence the response variable, namely the relevance of graduate work, data problems will be addressed first. Missing data on the job relevance of graduates is classified as MAR. MAR is data missing at random (MAR) or if there are systematic differences that only depend on the variables that are fully observed (Huisman, 2000). Data on the relevance of graduate employment with 9 predictor variables contains missing data on the variables study period (X_3), graduate waiting time (X_4), GPA of graduates (X_5), graduation on time (X_7), looking for or getting a job (X_8), and type of job (X_9). Table 1 shows details of respondents with missing data on each predictor variable:

Table 1. Identify Missing Data

No.	Predictor Variables	Respondent
1	study period (X_3)	33, 78, 84, 91, 95, 107
2	graduate waiting time (X_4)	25, 28, 73, 111, 118
3	GPA of graduates (X_5)	26, 104, 111, 125
4	graduation on time (X_7)	33, 78, 84, 91, 95, 107
5	looking for or getting a job (X_8)	111, 118
6	type of job (X_9)	111, 118

Efforts to handle missing data are shown in Table 1, namely using the single imputation method by filling in missing data for each respondent's entry in each predictor variable with the mode value. Based on equation (1) and processed using the single imputation method with R software, the following results were obtained:

Table 2. Results of the Single Imputation Method

	X_3	X_4	X_5	X_7	X_8	X_9
Modus	2	1	3	1	2	1

Multicollinearity

Next, a multicollinearity test will be carried out, namely to determine whether there is a linear relationship or correlation between significant predictor variables in the regression model. In ordinal logistic regression analysis, cases of multicollinearity are not permitted. In this study, to detect multicollinearity, based on obtaining equation (1) and using R software, VIF was obtained, with the following results:

Table 3. VIF Value

Variable	VIF Value
Gender (X_1)	1.0789
Scientific fields according to the study program (X_2)	1.2183
Study period (X_3)	1.3547
Graduate waiting time (X_4)	1.1898
GPA of graduates (X_5)	1.0514
Achievements while a student (X_6)	1.0765
Graduation on time (X_7)	1.1108
Looking for or getting a job (X_8)	1.1862
Type of job (X_9)	1.0994

The results obtained by the VIF value for each predictor variable are less than 10, so it can be concluded that there is no multicollinearity problem. It means that there is no strong correlation between the predictor variables. Because the non-multicollinearity assumption is met, it can be continued with model formation and parameter significance testing.

Ordinal Logistic Regression

Analysis is used to obtain a form of model estimation from the response variable with all significant predictor variables. Next, the best model was selected from the ordinal logistic regression analysis, estimating the parameters of the ordinal logistic regression model based on the odds ratio obtained. So that the best model from ordinal logistic regression is obtained, namely the estimation model for the nine predictor variables, using R software, the estimation results are obtained as follows:

Table 4. Parameter Estimation of the Ordinal Logistic Regression Model Relevance of Job Graduates According to Field of Job

Variable	Category	$(\hat{\beta})$	$SE(\hat{\beta})$	p-value	$Exp(\hat{\beta})$
Job relevance of graduates according to field of work	Constant (1)	17.8746	0.7833	$2.8596.10^{-115}$	$5.7921.10^{8}$
	Constant (2)	19.1604	0.8135	$1.1674.10^{-122}$	$2.0953.10^{8}$
Gender (X_1)	Female $_{(2)}$	0.3289	0.7360	0.6550	1.3894
Scientific fields according to the study program (X_2)	Mathematics Education $_{(2)}$	-2.4409	0.9048	0.0070	0.0871
	Indonesian Language and Literature Education $_{(3)}$	-2.5223	1.0374	0.0151	0.0803
	English Language Education $_{(4)}$	-0.7494	1.1331	0.5084	0.4726
	Primary Teacher Education $_{(5)}$	-0.0728	0.9325	0.9377	0.9298
Study period (X_3)	4.691 years $_{(2)}$	-17.0872	$9.925.10^{-8}$	0.000	$3.7942.10^{-8}$
	5 years $_{(3)}$	1.073	0.7738	0.1655	2.9241
	6 years $_{(4)}$	0.1109	1.3788	0.9359	1.1173
	7 years $_{(5)}$	3.1207	1.8506	0.0917	22.6625
Graduate waiting time (X_4)	< 6 month $_{(1.197)}$	-18.5692	$6.0946.10^{-8}$	0.000	$8.6202.10^{-9}$
	6-18 months $_{(3)}$	-0.5680	0.7546	0.4516	0.5667
	>18 months $_{(4)}$	-15.1751	$1.8580.10^{-8}$	0.000	$2.5676.10^{-7}$
GPA of graduates (X_5)	3.01-3.50 $_{(3)}$	17.1909	0.5439	$2.7652.10^{-219}$	$2.9236.10^{7}$
	3.406 $_{(3.406)}$	18.3238	1.0405	$2.0603.10^{-69}$	$9.0768.10^{7}$
	3.51-4.00 $_{(4)}$	17.1321	0.5382	$2.5552.10^{-222}$	$2.7565.10^{7}$
Achievements while a student (X_6)	Not Have $_{(2)}$	0.4216	0.6312	0.5042	1.5244
Graduation on time (X_7)	Didn't graduate on time $_{(2)}$	-0.2398	0.6652	0.7184	0.7868
Looking for or getting a job (X_8)	Before $_{(1.508)}$	-0.2089	$3.7323.10^{-8}$	0.000	0.8115
	After $_{(2)}$	1.4686	0.6592	$2.5882.10^{-2}$	4.3432
Type of job (X_9)	Permanent $_{(2)}$	-2.5411	0.7332	$5.2907.10^{-4}$	$7.8781.10^{-2}$

Based on Table 4, it can be seen that there are two intercept values (constants). This is due to the three classifications of the response variable, so there are two logit models. Next, parameter significance testing is carried out simultaneously and individually.

Concurrent Testing of Graduate Job Relevance Models

Simultaneous testing of the graduate job relevance model using the G^2 test using R software obtained the following results, which are in line with Equation (5), namely:

Table 5. Simultaneous Test with Likelihood Ratio

Model	G^2	Chi-Square	df	Decision	Information
Final	38.7688	31.4104	20	H_0 is rejected	There is an influence of the predictor variables on the response variable together

Based on Table 5, hypothesis testing with a significance level of 5%, the results obtained are that G^2 = 38.7688 > $X^2_{0.05;20}$=31.4104; which means H_0 is rejected and H_1 is accepted, meaning there is an influence of the predictor variables on the response variable together.

Next, several benchmarks were obtained from the coefficient of determination or R squared, which are shown in Table 6.

Table 6. Coefficient of Determination or R Squared Results

Model	Mc Faden	Cox and Snell	Nagelkerke
Final	0.2330	0.2545	0.3552

Based on Table 5, the Nagelkerke value is 0.3552, or 35.52%. This means that the predictor variable can explain the response variable by 35.52%, while 64.48% is influenced by other factors that are not included in the testing factors.

Individual Test

From simultaneous testing, it is known that the model is significant or rejects H_0 which means that at least one parameter is significant. The test statistic used partially is the Wald test, according to the results obtained in Equation (6). This test is used to determine significant predictor variables. By using R software, individual test results were obtained using the Wald test, which can be seen in Table.

Based on the results, the relevant one (H_0 is rejected) is found in $X_{5;3}$, $X_{5;3.406}$, $X_{5;4}$, $X_{8;1.508}$, $X_{8;2}$, and $X_{9;2}$. and thus, 3 predictor variables influence the level of job relevance of FKIP UMPRI graduates. Because the response variable consists of three classifications, there are two logit models using predictor variables that influence the response variable. Furthermore, the model estimation and ordinal logistic regression probability estimation of the job relevance of FKIP UMPRI graduates can be formed as follows:

$$\begin{aligned}\log it\,[\gamma_1] = 17.8746 &+ 0.3289X_{1;2}\\ &+ (-2.4409)X_{2;2}\\ &+ (-2.5223)X_{2;3}\\ &+ (-0.7494)X_{2;4}\\ &+ (-0.0728)X_{2;5}\\ &+ (-17.0872)X_{3;1.691}\\ &+ 1.0730X_{3;2} + 0.1109X_{3;3}\\ &+ 3.1207X_{3;4}\\ &+ (-18.5692)X_{4;1.197}\\ &+ (-0.580)X_{4;2}\\ &+ (-15.1751)X_{4;3}\\ &+ 17.1909X_{5;3}\\ &+ 18.3238X_{5;3.406}\\ &+ 17.1321X_{5;4}\\ &+ 0.4216X_{6;2}\\ &+ (-0.2398)X_{7;2}\\ &+ (-0.2089)X_{8;1.508}\\ &+ 1.4686X_{8;2}\\ &+ (-2.5411)X_{9;2}\end{aligned}$$

and

$$\begin{aligned}\log it\,[\gamma_1] = 19.1603 &+ 0.3289X_{1;2}\\ &+ (-2.4409)X_{2;2}\\ &+ (-2.5223)X_{2;3}\\ &+ (-0.7494)X_{2;4}\\ &+ (-0.0728)X_{2;5}\\ &+ (-17.0872)X_{3;1.691}\\ &+ 1.0730X_{3;2} + 0.1109X_{3;3}\\ &+ 3.1207X_{3;4}\\ &+ (-18.5692)X_{4;1.197}\\ &+ (-0.580)X_{4;2}\\ &+ (-15.1751)X_{4;3}\\ &+ 17.1909X_{5;3}\\ &+ 18.3238X_{5;3.406}\\ &+ 17.1321X_{5;4}\\ &+ 0.4216X_{6;2}\\ &+ (-0.2398)X_{7;2}\\ &+ (-0.2089)X_{8;1.508}\\ &+ 1.4686X_{8;2}\\ &+ (-2.5411)X_{9;2}\end{aligned}$$

Table 7. Wald Test Statistics on Variable Components that Influence the Response Variable

Variable	Category	*W*	p value	Hypothesis (<0.05)	Conclusion
GPA of graduates (X_5)	3.01-3.50$_{(3)}$	31.6091	$2.7652.10^{-219}$	H_0 is rejected	Graduates with a GPA of 3.01-3.50 influence the level of job relevance
	3.406$_{(3.406)}$	17.6101	$2.0603.10^{-69}$	H_0 is rejected	Graduates with a GPA of 3.406 influence the level of job relevance
	3.51-4.00$_{(4)}$	31.8291`	$2.5552.10^{-222}$	H_0 is rejected	Graduates with a GPA of 3.51-4.00 influence the level of job relevance
Looking for or getting a job (X_8)	Before $_{(1.508)}$	$-5.5959.10^{6}$	0.000	H_0 is rejected	Looking for or getting a job before graduating affects the level of job relevance
	After $_{(2)}$	2.2279	$2.5882.10^{-2}$	H_0 is rejected	Looking for or getting a job right after graduating affects the level of job relevance
Type of job (X_9)	Permanent $_{(2)}$	-3.4656	$5.2907.10^{-4}$	H_0 is rejected	The permanent type of graduate employment influences the level of job relevance

Table 8. Odds Ratio on Predictor Variables that Influence the Response Variable

Variable	Category	Odds Ratio	Information
GPA of graduates (X_5)	3.01-3.50$_{(3)}$	$2.9237.10^{7}$	For the GPA variable in the 3.01-3.50 category, the odds ratio value is $2.9237.10^{7}$, meaning that graduates with this GPA have a $2.9237.10^{7}$ times greater tendency to have a level of job relevance
	3.406$_{(3.406)}$	$9.0768.10^{7}$	For the GPA variable category 3.406, the odds ratio value is $9.0768.10^{7}$, meaning that graduates with this GPA have a $9.0768.10^{7}$ times greater tendency to have a level of job relevance
	3.51-4.00$_{(4)}$	$2.7565.10^{7}$	For the GPA variable in the 3.51-4.00 category, the odds ratio value is $2.7565.10^{7}$, meaning that graduates with this GPA have a $2.7565.10^{7}$ times greater tendency to have a level of job relevance
Looking for or getting a job (X_8)	Before $_{(1.508)}$	0.8115	For the variable looking for or getting a job before, the odds ratio value is 0.8115, meaning that graduates who are looking for or getting a job before have a 0.8115 times greater tendency to have a job relevance level
	After $_{(2)}$	4.3432	for the variable looking for or getting a job after getting an odds ratio value of 4.3432, meaning that graduates who are looking for or getting a job after have a 4.3432 times greater tendency to have a job relevance level
Type of job (X_9)	Permanent $_{(2)}$	0.0788	For the permanent job type variable, the odds ratio value is 0.0788, meaning that graduates with permanent job types have a 0.0788 times greater tendency to have a level of job relevance

Interpretation of Ordinal Logistic Regression Model Coefficients

Based the odds ratio from Equation (8), the results obtained are as stated in Table 4, and the results obtained are stated in Table 7, where there are $X_{5;3}$, $X_{5;3,406}$, $X_{5;4}$, $X_{8;1,508}$, $X_{8;2}$, and $X_{9;2}$ which is significant in the 3 predictor variables that influence the level of job relevance of FKIP UMPRI graduates, then the results of obtaining the odds ratio for the three predictor variables can be stated as follows:

CONCLUSIONS AND SUGGESTIONS

Based on data analysis and discussion, it can be stated that the results of the data description provide information that 80.3% of graduates have a high level of job relevance, 11.4% of graduates have a medium level of job relevance, and 8.3% of graduates have a low level of job relevance. Furthermore, the results of ordinal logistic regression using the odds proportion model showed that the predictor variable for graduate GPA was in the 3.01-3.50 category; 3,406; and 3.51-4.00; the predictor variable of looking for or getting a job either before or after; and the predictor variable of permanent job type had a significant influence on the level of job relevance of graduates.

As for further research, this research data has the potential to be analyzed using other statistical methods, which can be developed into other research results by taking into account hypotheses and other relevant research results. Therefore, it is hoped that the next author can further analyze the research data using other statistical methods.

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