JURNAL MATEMATIKA, STATISTIKA DAN KOMPUTASI e–ISSN: 2614–8811
Published by Departement of Mathematics, Hasanuddin University, Indonesia
https://journal.unhas.ac.id/index.php/jmsk/index
Vol. 20, No. 3, May 2024, pp. 606-622
DOI: 10.20956/j.v20i3.33220

Analysis of Academic Hardiness Factors Affecting Student Emotional Exhaustion in Malang Using Logit and Probit Models

Siti Nuradilla
Department of Mathematics, Faculty of Mathematics and Natural Sciences, Universitas Negeri Malang, Malang, Indonesia
***Email**:siti.nuradilla1903126@students.um.ac.id*

Received: 29 February 2024, revised: 1 April 2024, accepted: 2 April 2024

Abstract
The prevalence of emotional exhaustion as an indication of academic burnout among students during online learning is very high. Responding to the issues and neglect of studies on academic burnout, it is necessary to analyze the factors of academic hardiness among students in Malang City regarding emotional exhaustion. The ordinal probit regression model yields the best fit with 120 samples in analyzing the factors of academic hardiness on emotional exhaustion due to its smaller AIC value. Significant factors affecting emotional exhaustion are commitment to academic tasks (X_1), control over struggle (X_3), and control individual difficulties (X_4). The ordinal probit regression model obtained is $Z_1 = -1{,}028 - 0{,}153X_1 + 0{,}171X_3 - 0{,}239X_4$ and $Z_2 = 0{,}686 - 0{,}153X_1 + 0{,}171X_3 - 0{,}239X_4$. The marginal effect states that for every one-unit change in the ratio X_1 will increase students low emotional exhaustion by 0.016, and decrease students moderate emotional exhaustion by 0.044, and high emotional exhaustion by 0.060. Every one-unit change in the ratio X_3 will decrease students low emotional exhaustion by 0.018, and increase students moderate emotional exhaustion by 0.049, and high emotional exhaustion by 0.067. Every one-unit change in the ratio X_4 will increase students low emotional exhaustion by 0.025, and decrease students moderate emotional exhaustion by 0.070, and high emotional exhaustion by 0.095.

Keywords: *academic hardiness,* emotional exhaustion, ordinal logit regression, ordinal probit regression.

1. INTRODUCTION

Existing regression analysis is used among academics to see the effect of the predictor variable (X) on the response variable (Y), namely linear regression analysis. However, linear regression analysis is not appropriate when the response variable is categorical. The reason is that the assumption of homoscedasticity will be violated if using linear regression analysis, in which the response variable is measured on a continuous scale [8]. Therefore, one of the analyzes used when the response variable is categorical is logistic regression analysis. When viewed from the portrait of the response variables, logistic regression is divided into binary logistic regression, multinomial logistic regression, and ordinal logistic regression. The ordinal logistic regression model is also called the cumulative logit model.

Conversely, categorical-type response variables can be analyzed using the probit regression, complementary log-log, chaucit, and negative log-log regression methods [1]. This method is adjusted to the distribution of the analyzed data. Logit is used for most of the data distribution, probit is used for normal data distribution, complementary log-log is used for data that tends to be of high value, negative log-log is used for data that tends to be of low value, while chauchit is used if the latent variable is of extreme value.

Several pieces of research related to the application of ordinal logistic regression include research related to the application of ordinal logistic regression to the determinants of the academic stress level of STIS level I students [30] and research to determine the factors that influence the stress level of students in completing the thesis [13]. On the other hand, research related to comparative regression methods in resolving data with categorical type response variables has also been carried out, including logit, probit, and complementary log-log modelling on female labour force participation in the economy in East Kalimantan in 2019 [33], analysis of the factors that affect the human development index (IPM) using ordinal logistic regression and ordinal probit regression methods [26]. Unfortunately, these studies did not fully examine the separation of parameter estimators through the MLE approach in each method used. For example, suppose the probit, complementary log-log, chaucit, and negative log-log regression method with the MLE approach that results in non-convergence are applied. In that case, it can lead to an underestimate in one of the events so that the resulting coefficient will be biased.

Data analysis with categorical type variables is often used in social problems. For example, a social phenomenon still hotly discussed in the world, especially in Indonesia, is the spread of the coronavirus variant, which impacts education. In addition, the impact of online learning has created obstacles that result in students not understanding the lesson well, causing academic pressure, frustration, and stress which were included in the phenomenon of academic burnout [27]. The essence of academic burnout refers to stress, psychological factors caused by emotional exhaustion, depersonalization, and feelings of low personal achievement [35]. On the other, exhaustion in some phenomena is strongly influenced by cognitive exhaustion, physical exhaustion, and emotional exhaustion [6]. In line with this, emotional exhaustion is the most vital factor affecting academic burnout.

The phenomenon of academic burnout marked by academic stress is following research on 204 FISIP students at Mulawarman University, which showed 33.9% of students experienced high academic stress, 39.2% experienced moderate academic stress, 21.5% experienced low academic stress, and 5.4% experienced very low academic stress [23]. These results reflect that academic burnout has become a trend in the world of education amid the limitations of the learning system during the Covid-19 pandemic. The higher the academic burnout, the worse a person deals with academic problems [29]. If academic burnout continues, there will be a decline in student achievement and abilities.

The government is still negligent in responding to the psychological condition of students, primarily academic burnout. Several types of research in overcoming academic burnout during the Covid-19 pandemic include parental strategies to prevent academic burnout [2] and the effect of social support in predicting academic burnout in students [24]. The solutions offered tend to come from outside the individual. Academic hardiness as an internal intervention reduces stress levels for final-year students in doing a thesis [23]. This phenomenon is the basis of the importance of studying the influence of academic hardiness on emotional exhaustion as a factor that significantly influences academic burnout.

It is responding to the problems and neglect of studies on academic burnout, so necessary to analyze the factors of academic hardiness of students in Malang City on emotional exhaustion as the highest indication of individuals experiencing academic burnout. The analysis will be studied using logistic and probit regression methods because it has the appropriate data distribution criteria. Moreover, the accuracy of parameter estimation in formulating the best model is a highly considered study for a further selection of the best model. The objectives achieved through this research are: (1). Identifying academic hardiness factors that affect students' emotional exhaustion in Malang City; and (2). Knowing the influence model of academic hardiness factors in reducing students' emotional exhaustion level in Malang City.

2. METHODOLOGY

This type of research is correlational quantitative to model the relationship obtained from the study of the phenomenon of emotional exhaustion. This study uses primary data from research subjects, namely students studying in Malang City from Universitas Negeri Malang, Universitas Brawijaya, UIN Maulana Malik Ibrahim, and Universitas Muhammadiyah Malang, with a total of 120 students observing. The sampling technique used in this research is non-probability sampling with purposive sampling. Purposive sampling is a method based on specific criteria so that the data taken is more representative[36].

The instrument used in this study was a questionnaire to measure students' emotional exhaustion and academic hardiness. The response variable in this study was exhaustion exhaustion (Y) which adopted the Maslach Burnout Inventory: Students Survey (MBI-SS) diagnostic measure [38]. The author categorizes academic burnout low, medium, and high, respectively, with the labels "1", "2", and "3". While the predictor variables in this study were the academic hardiness scale consisting of X_1 (commitment to coursework), X_2 (commitment to priority setting), X_3 (control over the struggle), X_4 (management facing difficulties), X_5 (self-adjustment), and X_6 (course challenges) [10]. The data analysis techniques used are described as follows:

2.1 Descriptive Analysis

Descriptive analysis was conducted to see the general description of the data on the characteristics of academic burnout and the variables to be analyzed using ordinal logistic regression. The representation of descriptive analysis is done by displaying a table.

2.2 Multicollinearity Test

The multicollinearity test is part of the classical assumption test to determine the intercorrelation between independent variables [34]. A good regression model is characterized by the absence of intercorrelation between independent variables (no multicollinearity symptoms occur). One of the most credible ways to detect multicollinearity symptoms is using the tolerance and VIF (variance inflation factor) methods. The hypotheses used are:

- H_0: the independent variable is multicollinearity (VIF $\leq$ 10) or (tolerance < 0.10).
- H_1: the independent variable is not multicollinearity (VIF $\geq$1 0) or (tolerance > 0.10).

2.3 Ordinal Logistic Regression

The ordinal logistic regression model is also called the cumulative logit model. The response to the cumulative logit model is in the form of stratified data with J categories of response variables [14]. In the cumulative logit model, if there are J categories of response variables, then $J-1$ cumulative logit models will be obtained. If Y is an ordinal scale response variable then based on [1] the cumulative probability, namely $\boldsymbol{P(Y \leq j \mid x_i)}$ is represented as follows:

$$P(Y \leq j \mid x_i) = \frac{e^{(\alpha_j + \sum_{k=1}^{m} \beta_k x_{ik})}}{1+e^{(\alpha_j + \sum_{k=1}^{m} \beta_k x_{ik})}} \tag{2.1}$$

The logit model formed is as follows:

$$logit[P(Y \leq j| \, x_i)] = \ln\left(\frac{P(Y \leq j| \, x_i)}{1-P(Y \leq j| \, x_i)}\right) = \ln\left[e^{\alpha_j + \beta_1 X_1 \ldots + \beta_k X_k}\right] = \alpha_j + \sum_{k=1}^{m} \beta_k x_{ik} \tag{2.2}$$

The opportunities for each response category with three categories in this study are as follows:

$$\begin{aligned} p_1(x_i) &= P(Y \leq 1|x_i) = \frac{e^{(\alpha_1 + \sum_{k=1}^{m} \beta_k x_{ik})}}{1 + e^{(\alpha_1 + \sum_{k=1}^{m} \beta_k x_{ik})}} \\ p_2(x_i) &= P(Y \leq 2|x_i) - P(Y \leq 1|x_i) = \frac{e^{(\alpha_2 + \sum_{k=1}^{m} \beta_k x_{ik})}}{1+e^{(\alpha_2 + \sum_{k=1}^{m} \beta_k x_{ik})}} - \frac{e^{(\alpha_1 + \sum_{k=1}^{m} \beta_k x_{ik})}}{1+e^{(\alpha_1 + \sum_{k=1}^{m} \beta_k x_{ik})}} \\ p_3(x_i) &= P(Y \leq 3|x_i) - P(Y \leq 2|x_i) = \frac{1}{1+e^{(\alpha_2 + \sum_{k=1}^{m} \beta_k x_{ik})}} \end{aligned} \tag{2.3}$$

with p as probability, $j = 1,2,3, \ldots J$ as response variable category, $k = 1,2,3, \ldots m$ as predictor variable, x_{ik} as ith observation value with $i = 1,2,3 \ldots\ N$ of each predictor variable, α_j is the intercept parameter, β_k is the regression coefficient or slope parameter.

The method used to interpret the logistic regression parameters of categorical variables is by calculating the odds ratio (OR) [5]. The odds ratio for the predictor variable is defined as the relative amount in which the probability of an outcome increases (opportunity ratio > 1) or (opportunity ratio < 1) decreases when the predictor variable value increases by 1 unit [18]. The odds ratio in the $Y \leq j$ category as a comparison of $x_i = 1$ and $x_i = 0$ are:

$$OR = \frac{(P \leq j|1)/(P > j|1)}{(P \leq j|0)/(P > j|0)} = \frac{\exp(a_j + \beta_i)}{\exp(a_j)} = \exp(\beta_i) \tag{2.4}$$

In connection with the above, the value of the odds ratio can also be expressed by $e^{(coefficients\ of\ predictor\ variables)}$ [18].

2.4 Ordinal Probit Regression

Ordinal probit regression is one of the methods used to explain the relationship between response variables of ordinal type and predictor variables in the form of discrete, continuous variables or a combination of the two. Probit regression is a regression method that deals with probability units. Probit regression is often known as the Normit model (normal probability unit), based on the standard cumulative normal probability distribution function. The probit regression modelling is represented as follows [16].

$$Y^* = x^T \beta + \varepsilon \tag{2.5}$$

According to the above formula, Y^*: discrete response variable, β: coefficient parameter vector with $\beta = [\beta_1 \ \ \beta_2 \ \ldots \ \beta_p]^T$, x: independent variable vector with $x = [X_1 \ \ X_2 \ \ldots \ X_p]^T$, and ε: error assumed to be distributed $N(0, \sigma^2)$.

Equation (2.5) is transformed into the form $Z = \frac{Y^* - x^T\beta}{\sigma}$, in this case, $Z \sim N(0,1)$ then Y^* is categorized in an ordinal way. This categorization is that $Y^* \leq \gamma_1$ is categorized by $Y = 1$, $\gamma_1 \leq Y^* \leq \gamma_2$ is categorized by $Y = 2$,while $\gamma_{j-1} \leq Y^* \leq \gamma_j$ is categorized by $Y = j$, so that the ordinal probit regression model is obtained with $Y = 1$ for the lowest category and $Y = j$ for the highest category and $\phi(Z)$ as cumulative distribution function of normal distribution, namely:

$$\begin{gathered} P(Y=1) = P\,(z \leq \alpha_1 - x_i\beta) = \Phi(\alpha_1 - x_i\beta) \\ P(Y=2) = P\,(\alpha_2 - x_i\beta \leq z \leq \alpha_1 - x_i\beta) = \Phi(\alpha_2 - x_i\beta) - \Phi(\alpha_1 - x_i\beta) \\ P(Y=3) = 1 - P\,(z \leq \alpha_2 - x_i\beta) = 1 - \Phi(\alpha_2 - x_i\beta) \end{gathered} \tag{2.6}$$

The interpretation of the ordinal probit regression model uses marginal effects [16]. Marginal effect is defined as the magnitude of the effect of each predictor variable which is significant to the probability of each category of response variables. The marginal effects expressing the magnitude of the influence of the independent variables on $P(Y=1)$, $P(Y=2)$, $P(Y=3)$ are stated below.

$$\begin{gathered} \frac{\partial P(Y=1)}{\partial x_i} = -[\phi(\alpha_1 - x_i\beta)]\beta \\ \frac{\partial P(Y=2)}{\partial x_i} = [\phi(\alpha_1 - x_i\beta) - \phi(\alpha_2 - x_i\beta)]\beta \\ \frac{\partial P(Y=3)}{\partial x_i} = [\phi(\alpha_2 - x_i\beta)]\beta \end{gathered} \tag{2.7}$$

where Y: *response variable*, α_J as intercept parameter, β: $k \times 1$ *vector of estimated parameters*, x_i: $1 \times k$ *vector of independent variables*, and ε: *error* which is assumed to have a standard normal distribution $N(0, \sigma^2)$.

2.5 Parameter Estimation

The logistic model and probit model is non-linear, so the most popular approach is maximum likelihood estimation (MLE) [18]. The first thing to do is define the likelihood function and carry out a transformation process that forms the log-likelihood function $l(\beta)$ [17].

The likelihood function $L(\beta)$ to form an ordinal logistic model is formed as follows:

$$\begin{aligned} L(\beta) = \\ \prod_{i=1}^{120} \Bigg\{ & \left(\frac{e^{(\alpha_1 + \sum_{k=1}^{m} \beta_k x_{ik})}}{1 + e^{(\alpha_1 + \sum_{k=1}^{m} \beta_k x_{ik})}} \right)^{y_{1i}} \left(\frac{e^{(\alpha_2 + \sum_{k=1}^{m} \beta_k x_{ik})}}{1 + e^{(\alpha_2 + \sum_{k=1}^{m} \beta_k x_{ik})}} - \right. \\ & \left. \frac{e^{(\alpha_1 + \sum_{k=1}^{m} \beta_k x_{ik})}}{1 + e^{(\alpha_1 + \sum_{k=1}^{m} \beta_k x_{ik})}} \right)^{y_{2i}} \left(\frac{1}{1 + e^{(\alpha_2 + \sum_{k=1}^{m} \beta_k x_{ik})}} \right)^{y_{3i}} \Bigg\} \end{aligned} \tag{2.8}$$

The log-likelihood function $l(\beta)$ in ordinal logistic regression is as follows:

$$\begin{aligned} l(\beta) = \ln[L(\beta)] = \\ \sum_{i=1}^{120} \Bigg\{ & y_{1i} \ln \left[\frac{e^{(\alpha_1 + \sum_{k=1}^{m} \beta_k x_{ik})}}{1 + e^{(\alpha_1 + \sum_{k=1}^{m} \beta_k x_{ik})}} \right] + \\ & y_{2i} \ln \left[\frac{e^{(\alpha_2 + \sum_{k=1}^{m} \beta_k x_{ik})}}{1 + e^{(\alpha_2 + \sum_{k=1}^{m} \beta_k x_{ik})}} - \frac{e^{(\alpha_1 + \sum_{k=1}^{m} \beta_k x_{ik})}}{1 + e^{(\alpha_1 + \sum_{k=1}^{m} \beta_k x_{ik})}} \right] + y_{3i} \ln \left[\frac{1}{1 + e^{(\alpha_2 + \sum_{k=1}^{m} \beta_k x_{ik})}} \right] \Bigg\} \end{aligned} \tag{2.9}$$

where α_j and $\beta_k$are the parameters to be estimated, y_{ji} is the response to the ith observation in the jth category, x_i is the value of the ith observation, and p_j is the probability of the jth response variable category. The estimated value can be found by differentiating the log-likelihood function $l(\beta)$ against β and equaling it to zero as follows:

$$\frac{\partial l(\beta)}{\partial \alpha_1} = \sum_{i=1}^{120}\left\{y_{1i} - (y_{1i}+y_{2i})\left[\frac{e^{(\alpha_1+\sum_{k=1}^{m}\beta_k x_{ik})}}{1+e^{(\alpha_1+\sum_{k=1}^{m}\beta_k x_{ik})}}\right] - y_{2i}\left[\frac{e^{(\alpha_1+\sum_{k=1}^{m}\beta_k x_{ik})}}{e^{(\alpha_2+\sum_{k=1}^{m}\beta_k x_{ik})} - e^{(\alpha_1+\sum_{k=1}^{m}\beta_k x_{ik})}}\right]\right\} = 0$$
$$\frac{\partial l(\beta)}{\partial \alpha_2} = \sum_{i=1}^{120}\left\{y_{2i}\left[\frac{e^{(\alpha_2+\sum_{k=1}^{m}\beta_k x_{ik})}}{e^{(\alpha_2+\sum_{k=1}^{m}\beta_k x_{ik})} - e^{(\alpha_1+\sum_{k=1}^{m}\beta_k x_{ik})}}\right] + y_{3i}\left[\frac{e^{(\alpha_2+\sum_{k=1}^{m}\beta_k x_{ik})}}{1+e^{(\alpha_2+\sum_{k=1}^{m}\beta_k x_{ik})}}\right]\right\} = 0 \quad (2.10)$$
$$\frac{\partial l(\beta)}{\partial \beta_k} = \sum_{i=1}^{120}\left\{(y_{1i}+y_{2i})\sum_{k=1}^{m}x_{ik}\left[\frac{1}{1+e^{(\alpha_1+\sum_{k=1}^{m}\beta_k x_{ik})}}\right] + y_{3i}\sum_{k=1}^{m}x_{ik}\left[\frac{e^{(\alpha_2+\sum_{k=1}^{m}\beta_k x_{ik})}}{1+e^{(\alpha_2+\sum_{k=1}^{m}\beta_k x_{ik})}}\right]\right\} = 0$$

The likelihood function $L(\beta)$ to form an ordinal probit model is formed as follows:

$$L(\beta) = \prod_{i=1}^{120}\left\{\left(\Phi(\alpha_1 - x_i\beta)\right)^{y_{1i}}\left(\Phi(\alpha_2 - x_i\beta) - \Phi(\alpha_1 - x_i\beta)\right)^{y_{2i}}\left(1-\Phi(\alpha_2 - x_i\beta)\right)^{y_{3i}}\right\} \quad (2.11)$$

The log-likelihood function l(β) in ordinal probit regression is as follows:

$$l(\beta) = \ln[L(\beta)] = \sum_{i=1}^{120}\{y_{1i}\ln[\Phi(\alpha_1 - x_i\beta)] + y_{2i}\ln[\Phi(\alpha_2 - x_i\beta) - \Phi(\alpha_1 - x_i\beta)] + y_{3i}\ln[1-\Phi(\alpha_2 - x_i\beta)]\} \quad (2.12)$$

where α_j and β_k are the parameters to be estimated, y_{ji} is the response to the ith observation in the jth category, and x_i is the value of the ith observation. The estimated value can be found by differentiating the log-likelihood function $l(\beta)$ against β and equalizing it to zero as follows.

$$\frac{\partial l(\beta)}{\partial \alpha_j} = \sum_{i=1}^{120}\left\{\left(\frac{y_{ji}\phi\,(\alpha_j - x_i\beta)\Phi(\alpha_j - x_i\beta)x_i}{\Phi(\alpha_1 - x_i\beta)}\right)x_i\right\} = 0$$
$$\frac{\partial l(\beta)}{\partial \beta_k} = \sum_{i=1}^{120}\left\{\left(\frac{y_{ji}\phi\,(\alpha_j - x_i\beta)\Phi(\alpha_j - x_i\beta)x_i}{\Phi(\alpha_1 - x_i\beta)}\right)x_i\right\} = 0 \quad (2.13)$$

The estimated value can be found by differentiating the log-likelihood function $l(\beta)$ against β and equating it to zero. The results of partial differentiation from the above equation are non-linear and difficult to solve manually, so the Newton-Raphson iteration method is used in solving parameter estimates by finding the maximum estimate of each parameter. The Newton-Raphson method is more secure than other methods, so it is more effective [15]. Based on [11], the equations of the Newton-Raphson method in obtaining parameter estimates are:

$$\hat{\beta}^{s-1} = \hat{\beta}^{s} - [H^s]^{-1}g^s \quad (2.14)$$

Based on the above formula, s is the number of iterations, $[H^s]^{-1}$ is the diversification matrix, H^s is defined as the 2nd partial differentiation matrix of the log-likelihood function of the parameter and g^s as the first partial derivative matrix of the log-likelihood function of the parameter. These matrices are described as follows:

$$H^s = \frac{\partial^2 l(\beta)}{\partial\beta_{Jk}\partial\beta_{Jk}} = X^t V^s X \quad (2.15)$$
$$g^s = \frac{\partial l(\beta)}{\partial\beta_{Jk}} = X^t(Y - \pi^s) \quad (2.16)$$

The Newton-Raphson iteration process consists of determining the initial value of the parameter estimator (β^s), forming an X matrix of size $n\,(p+1)$ and a Y matrix of size $n*1$, determining the regression model, defining the matrix V^s, substitute the matrices H^s and g^s

where π^s is $n\,x\,1$ in the equation $\hat{\beta}^{s-1} = \hat{\beta}^s - [H^s]^{-1} g^s$. If the value of $\hat{\beta}^{s-1}$ is known, then calculate $\hat{\beta}^{s-1} - \beta^s$ and if $\hat{\beta}^{s-1} - \beta^s \ < \ \varepsilon = 1\,x\,10^{-6}$ then $\hat{\beta}^{s-1}$ is parameter estimation results and iterations are carried out until the value of β becomes convergent, the convergence limit in this case is $|\widehat{\beta}^{s-1} - \beta^s| < \varepsilon$ [3].

2.6 Model Significance Test with Model Fitting Information

The significance test of the model is used to compare whether the model is better with independent variables or without independent variables [21]. Significance is jointly carried out by reviewing the value of -2 log-likelihood or G statistic. The hypotheses to be tested are $H_1: \beta_1 = \beta_2 = \cdots = \beta_p = 0$ and H_0: at least there is one $\beta_p \neq 0$.

2.7 Simultaneous Parameter Estimator Test

The process of knowing whether the estimated predictor variable parameters obtained have a significant effect on the model or not can be done through the parameter significance test of the predictor variables. The parameter significance test consists of a simultaneous model parameter significance test and a partial model significance test. The simultaneous test of the significance of the model parameters was carried out with the likelihood ratio test [18]. This test is carried out with the following formula:

$$G = -2\ln\left[\frac{\left(\frac{n_j}{n}\right)^{n_j}\left(\frac{n_{j-1}}{n}\right)^{n_{j-1}} \ldots \left(\frac{n_2}{n}\right)^{n_2}\left(\frac{n_1}{n}\right)^{n_1}}{\prod_{i=1}^{n}[p_1(x_i)^{y_{1i}}][p_2(x_i)^{y_{2i}}]\ldots[p_J(x_i)^{y_{ji}}]}\right] \tag{2.17}$$

Where $n_1 = \sum_{i=1}^{n} y_{1i}$; $n_2 = \sum_{i=1}^{n} y_{2i}$; $n_j = \sum_{i=1}^{n} y_{ji}$; and $n = n_1 + n_1 + n_j$. y_{ji} is the response to the ith observation in the jth category, x_i is the value of the ith observation, and p_j is the probability of the jth response variable category. The hypotheses of this test are:

- $H_0: \beta_1 = \beta_2 = \cdots \beta_p = 0$
- $H_1: there\ is\ at\ least\ one\ \beta_p \neq 0.$

The test criteria are taking $\alpha = 0.05, H_0$ is rejected if $G > \chi^2{}_{(a;v)}$ where v is the number of predictor variables or the $p - value\ < \alpha$. This means that there is at least one predictor variable that influences the response variable.

2.8 Partial Parameter Estimator Test

The partial significance test of the model was carried out to determine the significance of the predictor variables to the model using the Wald Test [18]. The hypotheses used are:

- $H_0: \beta_j = 0$ with $k = 1,2,\ldots,r$ (the parameters for the k predictor variable are not significant)
- $H_1: \beta_j \neq 0$ with $k = 1,2,\ldots,r$ (parameters for the significant k predictor variable)

The test statistics used in the partial test are:

$$W^2 = \left[\frac{\widehat{\beta}_i}{SE(\widehat{\beta}_i)}\right]^2 \sim X^2{}_{(a,1)} \quad (2.18)$$

$\hat{\beta}_i$ is the parameter estimate of β_i while $SE(\hat{\beta}_i)$ is the standard error of the parameter estimate of β_i. The test criteria take the significance level, then H_0 is rejected if $W^2 > X^2{}_{(a,1)}$ or *p-value* $< \alpha$, then the *k*-th predictor variable affects the response variable.

2.9 Model Feasibility Test (Goodness of Fit Test)

The feasibility test of the model is carried out using Deviance test and Pearson test statistics to find out whether the model is feasible to use or not [12]. The hypotheses used are H_0: the model fits the data and H_1: the model does not fit the data. The Deviance test formula is represented as follows:

$$\text{D} = 2\sum_{k=1}^{g}\sum_{j=1}^{m} Y_{kj} \ln\left(\frac{Y_{kj}}{n\hat{p}_j(X_k)}\right) \quad (2.19)$$

and the Pearson test formula is represented as follows:

$$\text{P} = \sum_{k=1}^{g}\sum_{j=1}^{m} \left(\frac{Y_{kj}-\hat{p}_j(X_k)}{\hat{p}_j(X_k)}\right)^2 \quad (2.20)$$

With the following information:

- $\hat{p}_j(X_k)$: the probability of occurrence of the j response variable
- Y_{kj} : observation of the j response variable

The decision criteria taken are H_0 rejected if $D_{count} > X^2{}_{a;df}$ or $p - value < \alpha$ then the model does not match the data, so the model is not suitable for use.

2.10 Akaike's Information Criterion (AIC)

Akaike found a relationship between maximum likelihood (statistical analysis) and Kullback-Leibler divergence (information theory), thus defining the criteria for selecting a model known as Akaike's Information Criterion (AIC) [28]. Selection of the best model based on AIC criteria by choosing the model with the smallest AIC value. The AIC formula is described as follows:

$$AIC(P^*) = \frac{-2\ln L(P^*)}{N} + \frac{2p^*}{N} \quad (2.21)$$

Where $L(P^*)$ is the maximum likelihood value containing p^* predictor variables, p^* is the number of parameters $\boldsymbol{\beta}$ with $p^* = 0,1,2,\dots,r$ and N is the number of samples.

2.11 Apparent Error Rate (APER)

The formula used in calculating the APER value is described as follows:

$$APER = \frac{The\ number\ of\ misclassified\ samples}{The\ total\ number\ of\ samples}\ x\ 100\% \quad (2.22)$$

The model's classification accuracy value is determined by subtracting 100% from the APER value. The smaller APER value shows the classification accuracy [25].

3. RESULT AND DISCUSSION

The data in this study was obtained from 120 student respondents from Universitas Negeri Malang, Universitas Brawijaya, UIN Maulana Malik Ibrahim, and Universitas Muhammadiyah Malang. The descriptive analysis contains each predictor variable's minimum, maximum, average, and standard deviation values. Based on analysis carried out using SPSS, the percentage of respondents experiencing low emotional exhaustion was 7.5%, moderate emotional exhaustion was 44.2%, and high emotional exhaustion was 48.3%. It can be seen that students tend to experience a high category of emotional exhaustion. In line with this, it is necessary to study the factors that influence reducing emotional exhaustion, in this case namely academic hardiness. Descriptive analysis of the predictor variables is described as follows.

Table 3.1 Descriptive Analysis Results

Variable	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**
X1	6.380	18.276	13.47569	2.925702
X2	7.011	18.370	13.70535	2.709953
X3	5.080	14.763	10.38189	2.147708
X4	3.914	13.263	8.87365	2.138864
X5	3.961	14.629	10.15864	2.320572
X6	3.917	13.742	9.34838	2.350693

Individuals with academic hardiness are willing to be involved in achieving challenging achievements, establish a strong commitment to the academic process, and have control over the process carried out [7]. On the other hand, it is known that the data is normally distributed with no trend in the values of one of the response variables so that the data analysis models that can be used are the ordinal logistic regression model and ordinal probit regression.

3.1 Multicollinearity Test

Table 3.2 Multicollinearity Test Results

Model (Constant)	**VIF**	***Tolerance***
X1	1.686	0.593
X2	1.585	0.631
X3	1.286	0.778
X4	1.999	0.500
X5	2.025	0.494
X6	1.236	0.809

Based on Table 2 the VIF value < 10 and the tolerance value > 0.10. The results indicate that the decision taken is to reject H_0 and accept H_1 so there are no multicollinearity symptoms.

3.2 Parameter Estimation

Parameter estimation in this study uses the maximum likelihood estimation (MLE) method. The parameter estimation results in the complementary log-log, negative log-log, and chaucit models do not converge in the 8th iteration. The results indicate an imperfect separation in the model, so it is prone to bias [3]. On the other hand, parameter estimation using logit and probit models converges on the 7th and 6th iterations, respectively. The results of the estimation of the parameters of the independent variable on the dependent variable of emotional exhaustion are described as follows.

Table 3.3 Parameter Estimation Results

	Logit Model	Probit Model
	Estimate	***Estimate***
-2 Log Likelihood	-1.764	-1.028
[Y=1]	1.171	0.686
[Y=2]	-0.258	-0.153
X1	0.140	0.091
X2	0.290	0.171
X3	-0.367	-0.239
X4	0.193	0.126
X5	0.092	0.052
X6	-1.764	-1.028

The initial ordinal logistic regression model is formed as follows:

a. Logit$[P(Y_i \leq 1|X_i] = -1.764 - 0.258X_1 + 0.140X_2 + 0.290X_3 - 0.367X_4 + 0.193X_5 + 0.092X_6$

b. Logit$[P(Y_i \leq 2|X_i] = 1.171 - 0.258X_1 + 0.140X_2 + 0.290X_3 - 0.367X_4 + 0.193X_5 + 0.092X_6$

The initial ordinal probit regression model is formed as follows:

a. $Z_1 = -1.028 - 0.153X_1 + 0.091X_2 + 0.171X_3 - 0.239X_4 + 0.126X_5 + 0.052X_6$

b. $Z_2 = 0.686 - 0.153X_1 + 0.091X_2 + 0.171X_3 - 0.239X_4 + 0.126X_5 + 0.052X_6$

3.3 Model Significance Test with Model Fitting Information

Table 3.4 Model fitting information (Logit Model)

Model	**Model Logit**			
	2 log-likelihood	**Chi-Square**	**df**	**Sig.**
Intercept Only	292.370			
Final	279.127	13.242	6	0.039

Table 3.5 Model fitting information (Probit Model)

Model	**Model Probit**			
	2 log-likelihood	**Chi-Square**	**df**	**Sig.**
Intercept Only	292.370			
Final	278.693	13.677	6	0.033

Based on the results of the model significance test on the dependent variable of emotional exhaustion, it is known that the -2 log-likelihood value of the model without independent variables is 292.370 while the -2 log-likelihood model with the independent variable is 279.127 and the G statistic value is 13.242. On the other hand, the result of the -2 log-likelihood of the probit model with the independent variable is 278.693 and the G statistic value is 13.677. Therefore, the test criteria were carried out by taking the significance level $\alpha = 0.05$ from the chi-square distribution table, it was obtained $X^2{}_{(0.05,6)} = 12.59$, while the G statistic value of the logit model was 13.242 (>12. 59) and the G statistic value of the probit model is 13.677 (> 12.59), therefore, rejecting H_0 implies that the model is significant.

3.4 Test the Significance of the Model with the Wald Test

The results of the Wald test can be seen in the following table.

Table 3.6 Wald Test Results

	Model Logit			**Model Probit**		
	Estimate	**Wald**	**Sig.**	**Estimate**	**Wald**	**Sig.**
X_1	-0.258	8.166	0.004	-0.153	8.672	0.003
X_2	0.140	2.426	0.119	0.091	3.002	0.083
X_3	0.290	7.176	0.007	0.171	7.359	0.007
X_4	-0.367	8.716	0.003	-0.239	10.968	0.001
X_5	0.193	2.919	0.088	0.126	3.620	0.057
X_6	0.092	1.073	0.300	0.052	0.984	0.321

The results of separate significance tests in the logit and probit models on the dependent variable emotional exhaustion illustrate that X_1, X_3, and X_4 significantly affect the level of emotional exhaustion of students studying in Malang City. The variables $X_2, X_5,$ and X_6 have no significant effect on the level of emotional exhaustion. Variables declared insignificant will be removed from the model and a new logistic regression equation will be formed. The new ordinal logistic regression model is obtained as follows.

$$\text{Logit } [P(Y_i \leq 1|X_i] = -1.764 - 0.258X_1 + 0.290X_3 - 0.367X_4$$
$$\text{Logit } [P(Y_i \leq 2|X_i] = 1.171 - 0.258X_1 + 0.290X_3 - 0.367X_4$$

Based on the Wald test results, the variables that have a significant effect on emotional exhaustion consist of X_1 (commitment to coursework), X_3 (control over the struggle), and X_4 (control in facing difficulties). The new ordinal probit model is formed as follows.

$$Z_1 = -1.028 - 0.153X_1 + 0.171X_3 - 0.239X_4$$
$$Z_2 = 0.686 - 0.153X_1 + 0.171X_3 - 0.239X_4$$

3.5 The Goodness of Fit Test

Table 3.7 The Goodness of Fit Test Results

	Model Logit			**Model Probit**		
	Chi-Square	**df**	**Sig.**	**Chi-Square**	**df**	**Sig.**
Pearson	201.398	232	0.927	195.905	232	0.959
Deviance	196.427	232	0.957	194.858	232	0.964

The goodness of fit test results on the logit model contain the Pearson P value $(201.398) < \chi^2{}_{0.05;232}(268.5)$, the Deviance D value $(196.427) < \chi^2{}_{0,05;232}(268.5)$ and the significance value is greater than $\alpha = 0.05$. The goodness of fit test results on the probit model contain the Pearson P value $(195.905) < \chi^2{}_{0.05;232}(268.5)$, the Deviance D value $(194.858) <$

${\chi^2}_{0,05;232}(268.5)$ and the significance value is greater than $\alpha = 0.05$. The decision taken is to fail to reject H_0 and reject H_1, meaning that the ordinal logit regression and the ordinal probit regression model obtained is suitable for use.

3.6 Akaike's Information Criterion (AIC)

The Akaike's Information Criterion (AIC) value for the ordinal logistic regression model is 212.427, while the AIC value for the ordinal probit regression model is 210.858. Based on these results, the best model used is ordinal probit regression.

3.7 Classification Accuracy Test

The evaluation process to determine the classification accuracy predicted by ordinal logit regression and ordinal probit regression was carried out using the Apparent Error Rate (APER) explained as follows.

Table 3.8 Apparent error rate (APER) Logit Model

Observation	Prediction			Sum
	Low	Moderate	High	
Low	0	0	0	0
Moderate	0	59	0	59
High	0	0	61	61
Sum	0	59	61	120

Table 3.9 Apparent error rate (APER) Probit Model

Observation	Prediction			Sum
	Low	Moderate	High	
Low	0	0	0	0
Moderate	0	56	0	56
High	0	0	64	64
Sum	0	56	64	120

Based on the classification accuracy table, the APER value obtained is 0%, so the classification accuracy value in the probit model is $(1 - APER)\ x\ 100\% = 100\%$. The accuracy of the classification states that the logit and probit models are very suitable for use.

3.8 Model Interpretation: Marginal Effects of Ordinal Probit Regression

The final ordinal probit regression model is known as follows:

$$Z_1 = -1{,}028 - 0{,}153X_1 + 0{,}171X_3 - 0{,}239X_4$$
$$Z_2 = 0{,}686 - 0{,}153X_1 + 0{,}171X_3 - 0{,}239X_4$$

The variables that have a significant influence, namely X_1 (commitment to coursework), X_3 (control over the struggle), and X_4 (controlling facing difficulties) is the part of academic hardiness that is most influential in overcoming emotional exhaustion. This is in accordance with research that emotional exhaustion is the highest indication of academic burnout [22]. This is consistent with the fact that hardiness makes individuals choose good strategies and be able to survive in difficult situations (self-control) [4] as well as viewing academic demands as challenging (commitment to tasks) and difficulties are not a threat (difficulty control) [37]. Interpretation of ordinal probit regression results is carried out through calculating marginal effect values. The marginal effect value of X_1 (commitment to coursework) on emotional exhaustion with $X_1 = 5.70$, $X_3 = 20.11$, and $X_4 = 13.23$.

- $\frac{\partial P(Y=1)}{\partial x_1} = -\beta_1(\phi(Z_1))$= $0.153\ \phi(-1.623) = 0.016$
- $\frac{\partial P(Y=2)}{\partial x_1} = \beta_1(\phi(Z_2) - \phi(Z_1)) = -0.153(\phi(0.090) - \phi(-1.623)) = -0.044$
- $\frac{\partial P(Y=3)}{\partial x_1} = \beta_1(\phi(Z_1)) = -0.153\ \phi(0.090) = -0.060$

It means that for every one-unit change in the ratio X_1 (commitment to academic tasks), it will increase the probability of students experiencing low emotional exhaustion by 0.016, and decrease the probability of students experiencing moderate emotional exhaustion by 0.044, and high emotional exhaustion by 0.060.

The marginal effect of X_3 (control over the struggle) on emotional exhaustion with $X_1 = 5.70$, $X_3 = 20.11$, and $X_4 = 13.23$ is described as follows:

- $\frac{\partial P(Y=1)}{\partial x_3} = -\beta_3(\phi(Z_1)) = -0{,}171\ \phi(-1{,}028 - 0{,}153X_1 + 0{,}171X_3 - 0{,}239X_4) = -0{,}018$
- $\frac{\partial P(Y=2)}{\partial x_3} = \beta_3(\phi(Z_2) - \phi(Z_1)) = 0{,}171(\phi(0{,}686 - 0{,}153X_1 + 0{,}171X_3 - 0{,}239X_4) - \phi(-1{,}028 - 0{,}153X_1 + 0{,}171X_3 - 0{,}239X_4))$=$0{,}049$
- $\frac{\partial P(Y=3)}{\partial x_3} = \beta_3(\phi(Z_2)) = 0{,}171\ \phi(0{,}686 - 0{,}153X_1 + 0{,}171X_3 - 0{,}239X_4) = 0{,}067$

It means that for every one-unit change in the ratio X_3 (control over the struggle), it will decrease the probability of students experiencing low emotional exhaustion by 0.018, and increase the probability of students experiencing moderate emotional exhaustion by 0.049, and high emotional exhaustion by 0.067.

The marginal effect of X_4 (control facing difficulties) on emotional exhaustion with X_1 = 7.731 and X_4 = 9.060 is described as follows:

- $\frac{\partial P(Y=1)}{\partial x_4} = -\beta_4(\phi(Z_1)) = 0{,}239\ \phi(-1{,}028 - 0{,}153X_1 + 0{,}171X_3 - 0{,}239X_4)$= $0{,}025$
- $\frac{\partial P(Y=2)}{\partial x_4} = \beta_4(\phi(Z_2) - \phi(Z_1)) = -0{,}239(\phi(0{,}686 - 0{,}153X_1 + 0{,}171X_3 - 0{,}239X_4) - \phi(-1{,}028 - 0{,}153X_1 + 0{,}171X_3 - 0{,}239X_4)) = -0{,}070$
- $\frac{\partial P(Y=3)}{\partial x_4} = \beta_4(\phi(Z_2)) = -0{,}239\ \phi(0{,}686 - 0{,}153X_1 + 0{,}171X_3 - 0{,}239X_4) = -0{,}095$

It means that for every one-unit change in the ratio X_4 (control facing difficulties), it will increase the probability of students experiencing low emotional exhaustion by 0.025, and decrease the probability of students experiencing moderate emotional exhaustion by 0.070, and high emotional exhaustion by 0.095.

The research results obtained indicate that descriptively the percentage of respondents experiencing low emotional exhaustion is 7.5%, moderate emotional exhaustion is 44.2%, and high emotional exhaustion is 48.3%. Therefore, it appears that students tend to experience high emotional exhaustion as the primary indication of Academic Burnout. These results are consistent with previous research indicating that online learning still presents significant challenges for students both psychologically and in terms of learning media [31] [9].

The research findings indicate that academic hardiness significantly impacts the level of emotional exhaustion among students, particularly in the context of online learning in the city of Malang during the Covid-19 pandemic. Unlike previous research, this study does not directly decide to use one regression model in examining the influence of academic hardiness on emotional exhaustion, but rather examines which model satisfies convergence on parameter estimators through the Maximum Likelihood Estimation (MLE) approach. If MLE approach is conducted in data analysis and results in separation, it can lead to estimation errors, thus the coefficients produced will be biased [32]. Based on the data analysis, the best-performing model that has been tested for convergence is represented by Ordinal Logistic Regression and Ordinal Probit Regression. The ordinal probit regression model is most effective in analyzing the relationship between academic hardiness factors and emotional exhaustion. This methodological choice is justified by its superior performance in terms of AIC values and classification accuracy compared to the logistic model, thus providing a more reliable tool for educators and policymakers to assess and address student well-being.

The results of the ordinal probit regression analysis indicate that commitment to academic tasks (X_1), control over struggles (X_3), and control over individual difficulties (X_4) are significant predictors of emotional exhaustion. The negative coefficients of $X_1, X_3, and\ X_4$ in the probit model indicate that higher academic resilience can decrease emotional exhaustion among students in Malang city. This means that an increase in commitment to coursework and better control over difficulties lead to a decrease in the likelihood of experiencing high emotional exhaustion. This is consistent with the research [4], which states that hardiness has a negative relationship with anxiety and academic procrastination [20]. These results underline the importance of psychological hardiness in significantly addressing challenges [39]. Academic hardiness emerges as an effective coping strategy among students to mitigate the adverse effects of emotional exhaustion and academic stress.

Although some studies indicate that ordinal logistic regression and ordinal probit regression share similarities in terms of model significance, the probit model is more suitable for examining the impact of each predictor variable on different levels of emotional exhaustion based on marginal effects [40] [19]. The marginal effect states that for every one-unit change in the ratio X_1 (commitment to academic tasks), it will increase the probability of students experiencing low emotional exhaustion by 0.016, and decrease the probability of students experiencing moderate emotional exhaustion by 0.044, and high emotional exhaustion by 0.060. Every one-unit change in the ratio X_3 (control over the struggle), it will decrease the probability of students experiencing low emotional exhaustion by 0.018, and increase the probability of students experiencing moderate emotional exhaustion by 0.049, and high emotional exhaustion by 0.067. Every one-unit change in the ratio X_4 (control facing difficulties), it will increase the probability of students experiencing low emotional exhaustion by 0.025, and decrease the probability of students experiencing moderate emotional exhaustion by 0.070, and high emotional exhaustion by 0.095.

3. CONCLUSION

The ordinal probit regression model is the best model to analyze the factors of academic hardiness on emotional exhaustion because it has an AIC value smaller than the logit model with a classification accuracy of 100%. The estimation of the probit model also converges faster in the 6th iteration than the logit model and there is no separation. Based on the ordinal probit regression analysis, students at Malang City campuses tend to experience high emotional exhaustion (48.3%). Factors that significantly affect emotional exhaustion are commitment to coursework and control over the difficulties faced by individuals. The ordinal probit regression model obtained is $Z_1 = -1{,}028 - 0{,}153X_1 + 0{,}171X_3 - 0{,}239X_4$ and $Z_2 = 0{,}686 - 0{,}153X_1 + 0{,}171X_3 - 0{,}239X_4$. The marginal effect states that for every one-unit change in the ratio X_1 (commitment to academic tasks), it will increase the probability of students experiencing low emotional exhaustion by 0.016, and decrease the probability of students experiencing moderate emotional exhaustion by 0.044, and high emotional exhaustion by 0.060. Every one-unit change in the ratio X_3 (control over the struggle), it will decrease the probability of students experiencing low emotional exhaustion by 0.018, and increase the probability of students experiencing moderate emotional exhaustion by 0.049, and high emotional exhaustion by 0.067. Every one-unit change in the ratio X_4 (control facing difficulties), it will increase the probability of students experiencing low emotional exhaustion by 0.025, and decrease the probability of students experiencing moderate emotional exhaustion by 0.070, and high emotional exhaustion by 0.095. Therefore, the research suggests that increased academic hardiness is likely to decrease heightened emotional exhaustion.

ACKNOWLEDGEMENT

Thanks to all parties who have participated as respondents and supervisors in the research. This work has also been supported by the Department of Mathematics, Faculty of Mathematics and Natural Science, Universitas Negeri Malang.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

REFERENCES

[1]. Agresti, A., 2007. An Introduction to Categorical Data Analysis, Second. ed. Wiley-Interscience, New York.
[2]. Agusriani, A., Fauziddin, M., 2021. Strategi Orangtua Mengatasi Kejenuhan Anak Belajar dari Rumah Selama Pandemi Covid-19. JO 5, 1729–1740. https://doi.org/10.31004/obsesi.v5i2.961
[3]. Allison, P.D., 2008. 360-2008: Convergence Failures in Logistic Regression 11.
[4]. Anjum, R., 2022. Role of Hardiness and Social Support in Psychological Well-Being Among University Students. MJESTP 89–102. https://doi.org/10.52634/mier/2022/v12/i1/2172
[5]. Ari, E., Yildiz, Z., 2014. Parallel Lines Assumption In Ordinal Logistic Regression And Analysis Approaches 1, vol. 1, no. 3, p. 17, 2014.
[6]. Asiwe, D.N., Jorgensen, L.I., Hill, C., 2014. The development and investigation of the psychometric properties of a burnout scale within a South African agricultural research institution. SA j ind psychol 40, 14 pages. https://doi.org/10.4102/sajip.v40i1.1194
[7]. Azizah, N., Kardiyem, 2020. Pengaruh Perfeksionisme, Konformitas, dan Media Sosial terhadap Prokrastinasi Akademik dengan Academic Hardiness sebagai Variabel Moderasi 14.
[8]. Bender, R., 1997. Ordinal Logistic Regression in Medical Research 6
[9]. Cahyawati, D., Gunarto, M., 2021. Persepsi mahasiswa terhadap pembelajaran daring pada masa pandemi Covid-19. jitp 7, 150–161. https://doi.org/10.21831/jitp.v7i2.33296
[10]. Cheng, Y.-H., Tsai, C.-C., Liang, J.-C., 2019. Academic hardiness and academic self-efficacy in graduate studies. Higher Education Research & Development 38, 907–921. https://doi.org/10.1080/07294360.2019.1612858

[11]. Christensen, J., Bastien, C., 2016. Chapter | three - Introduction to General Optimization Principles and Methods 62. https://doi.org/10.1016/B978-0-12-417297-5.00003-1
[12]. Fagerland, M.W., Hosmer, D.W., 2017. How to Test for Goodness of Fit in Ordinal Logistic Regression Models. The Stata Journal 17, 668–686. https://doi.org/10.1177/1536867X1701700308
[13]. Fatonah, L., Sanapiah, S., Febrilia, B.R.A., 2019. Regresi Logistik Ordinal (Studi Kasus Faktor Yang Mempengaruhi Tingkat Stres Mahasiswa Dalam Menyelesaikan Skripsi). Media. Pembelajaran. Matematika 5, 146. https://doi.org/10.33394/mpm.v5i2.1501
[14]. Giri, N.C., 2004. Multivariate statistical analysis, 2nd ed., rev.expanded. ed, Statistics, textbooks and monographs. Marcel Dekker, New York.
[15]. Gnetchejo, P.J., Ndjakomo Essiane, S., Dadjé, A., Ele, P., 2021. A combination of Newton-Raphson method and heuristics algorithms for parameter estimation in photovoltaic modules. Heliyon 7, e06673. https://doi.org/10.1016/j.heliyon.2021.e06673
[16]. Greene, W.H., 2003. Econometric analysis, 5th ed. ed. Prentice Hall, Upper Saddle River, N.J.
[17]. Hair, J.F., Black, W.C., Babin, B.J., Anderson, R.E., 2019. Multivariate data analysis, Eighth edition. ed. Cengage, Andover, Hampshire.
[18]. Hosmer, D.W., Lemeshow, S., Sturdivant, R.X., 2013. Applied logistic regression, Third edition. ed, Wiley series in probability and statistics. Wiley, Hoboken, New Jersey.
[19]. İşçi, Ö., Durmuş, B., İncekırık, A., 2022. Ordered Choice Models: Ordinal Logit and Ordinal Probit 6
[20]. Jia, J., Wang, L., Xu, J., Lin, X., Zhang, B., Jiang, Q., 2021. Self-Handicapping in Chinese Medical Students During the COVID-19 Pandemic: The Role of Academic Anxiety, Procrastination and Hardiness. Front. Psychol. 12, 741821. https://doi.org/10.3389/fpsyg.2021.741821
[21]. Kook, L., Herzog, L., Hothorn, T., Dürr, O., Sick, B., 2021. Deep and interpretable regression models for ordinal outcomes. arXiv:2010.08376 [cs, stat].
[22]. Koropets, O., Fedorova, A., Kacane, I., 2019. Emotional And Academic Burnout Of Students Combining Education And Work. Presented at the 11th International Conference on Education and New Learning Technologies, Palma, Spain, pp. 8227–8232. https://doi.org/10.21125/edulearn.2019.2038
[23]. Lubis, H., Ramadhani, A., Rasyid, M., 2021. Stres Akademik Mahasiswa dalam Melaksanakan Kuliah Daring Selama Masa Pandemi Covid 19. Psikostudia 10, 31. https://doi.org/10.30872/psikostudia.v10i1.5454
[24]. Muflihah, L., Savira, S.I., 2021. PENGARUH PERSEPSI DUKUNGAN SOSIAL TERHADAP BURNOUT AKADEMIK SELAMA PANDEMI. . Character 08, 11.
[25]. Nur'eni, N., Handayani, L., 2020. Regresi Probit untuk Analisis Variabel-Variabel yang Mempengaruhi Perceraian di Sulawesi Tengah. asks 12, 13. https://doi.org/10.34123/jurnalasks.v12i1.211
[26]. Nurmalasari, R., Ispriyanti, D., 2017. ANALISIS Faktor-Faktor Yang Mempengaruhi Indeks Pembangunan Manusia (Ipm) Menggunakan Metode Regresi Logistik Ordinal Dan Regresi Probit Ordinal 6, 10.
[27]. Pawicara, R., Conilie, M., 2020. Analisis Pembelajaran Daring terhadap Kejenuhan Belajar Mahasiswa Tadris Biologi IAIN Jember di Tengah Pandemi Covid-19. alveoli 1, 29–38. https://doi.org/10.35719/alveoli.v1i1.7
[28]. Portet, S., 2020. A primer on model selection using the Akaike Information Criterion. Infectious Disease Modelling 5, 111–128. https://doi.org/10.1016/j.idm.2019.12.010
[29]. Pratitis, N.T., Suroso, S., Cahyanti, R.O., Sa'idah, F.L.S., 2021. Self Regulated Learning dan Dukungan Sosial dengan Prokrastinasi Akademik pada Mahasiswa di Masa Pandemi. soshum 2, 1–7. https://doi.org/10.24123/soshum.v2i1.3953

[30]. Putri, N.I., Budyanra, B., 2020. Penerapan Regresi Logistik Ordinal Dengan Proportional Odds Model Pada Determinan Tingkat Stres Akademik Mahasiswa. semnasoffstat 2019, 368–378. https://doi.org/10.34123/semnasoffstat.v2019i1.104

[31]. Rondonuwu, V.W.K., Mewo, Y.M., Wungow, H.I.S., 2021. Pendidikan Kedokteran di Masa Pandemi COVID-19 Dampak Pembelajaran Daring Bagi Mahasiswa Fakultas Kedokteran Angkatan 2017 Unsrat. JBM 13, 67. https://doi.org/10.35790/jbm.13.1.2021.31764

[32]. Senaweera, O., S. Haddela, P., Dharmarathne, G., 2021. Effects of Random Sampling Methods on Maximum Likelihood Estimates of a Simple Logistic Regression Model. AJAMS 9, 28–37. https://doi.org/10.12691/ajams-9-1-5

[33]. Setyaningrum, D.A., Sirait, T., 2021. Pemodelan Logit, Probit, Dan Complementary Log-Log. semnasoffstat 2020, 429–438. https://doi.org/10.34123/semnasoffstat.v2020i1.383

[34]. Shrestha, N., 2020. Detecting Multicollinearity in Regression Analysis. AJAMS 8, 39–42. https://doi.org/10.12691/ajams-8-2-1

[[35]. Sokal, L., Trudel, L.E., Babb, J., 2020. Canadian teachers’ attitudes toward change, efficacy, and burnout during the COVID-19 pandemic. International Journal of Educational Research Open 1, 100016. https://doi.org/10.1016/j.ijedro.2020.100016

[36]. Sugiyono, 2019. Metode Penelitian & Pengembangan: Research and Development. Alfabeta, Bandung.

[37]. Wardani, R., 2020. Academic Hardiness, Skills, And Psychological Well-Being On New Student. Jurnal Psikologi 19, 188–200. https://doi.org/10.14710/jp.19.2.188-200

[38]. Yavuz, G., Dogan, N., 2014. Maslach Burnout Inventory-Student Survey (MBI-SS): A Validity Study. Procedia - Social and Behavioral Sciences 116, 2453–2457. https://doi.org/10.1016/j.sbspro.2014.01.590

[39]. Zhou, H., Chen, J., 2021. How Does Psychological Empowerment Prevent Emotional Exhaustion? Psychological Safety and Organizational Embeddedness as Mediators. Front. Psychol. 12, 546687. https://doi.org/10.3389/fpsyg.2021.546687

[40]. Zhou, J., Zheng, T., Dong, S., Mao, X., Ma, C., 2022. Impact of Helmet-Wearing Policy on E-Bike Safety Riding Behavior: A Bivariate Ordered Probit Analysis in Ningbo, China. IJERPH 19, 2830. https://doi.org/10.3390/ijerph19052830