

Analysis of factors affecting lecturer performance at a university during the COVID-19 pandemic using logistic regression and genetic algorithms

Sri Setyaningsih^{a,*} Postgraduate School, Pakuan University, Bogor, Indonesia

Sukono Sukono^b, Department of Mathematics, Faculty of Mathematics and Natural Sciences, Universitas Padjadjaran, Indonesia

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Abstract

The Covid-19 pandemic has forced us to change all aspects of our lives, including higher education. As a result, lecturers get an impact in terms of technology literacy obligations. This situation certainly affects their performance in implementing the Tri Dharma of Higher Education. The purpose of this study is to analyze the factors that affect the performance of lecturers during the Covid-19 pandemic. These factors include age, education, motivation, satisfaction, perception of appreciation, supervision, learning facilities, and technological literacy. The method for collecting data was questionnaires and open interviews with 150 lecturer respondents at a university. Furthermore, the data obtained were analyzed using a logistic regression model, where the parameter estimation was conducted using a genetic algorithm. The estimation process is assisted by Matlab 7.0 software. The results of the analysis show that the factors of age, education, motivation, satisfaction, perception of supervision, learning facilities, and technological literacy have a significant effect on lecturer performance. This study implies that the University needs to consider significant factors for improving lecturers' performance so that teaching and learning activities can run effectively.

Keywords: Covid-19, · teaching and learning, lecturer performance, Logistic regression, Genetic algorithm.

* ADDRESS OF CORRESPONDENCE: Sri Setyaningsih, Pakuan University, Postgraduate School, Bogor, Indonesia
Email address: sri_setya@unpak.ac.id

1. Introduction

Tri Dharma of Higher Education is the obligation of Higher Education to provide education, research, and community service (Law No. 12 of 2012, Article 1 Paragraph 9). In general, the Tri Dharma of Higher Education is one of the goals that every university in Indonesia must achieve and carry out. Higher education should give birth to young people or educated people who have high spirits, creative, independent, innovative thinking build the nation in various sectors according to their abilities.

However, since the outbreak of the Covid-19 pandemic, it has caused panic throughout Indonesia. After the central government successively reacted to the Covid-19 with various actions, such as determining the standby status, disaster emergency, unnatural disaster and extending the disaster emergency status and huge-scale social limitation (Kelana, 2020). The preventing of covid-19 has been implemented in terms of social and physical distancing policies in all aspects of life. These policies were regarding the number of confirmed cases that are gradually increasing day after day and the spread of the virus that become difficult to control all over Indonesia.

Through the Reference Letter of the Minister of Education and Culture of the Republic of Indonesia Number 3 the Year 2020 on Prevention of Covid-19 in Education Unit, all higher education institutions in Indonesia, take firm action on the government's appeal to do learning activities from home (Arifudin, 2020). All academic activities probably conducted on the campus need to be conducted from home during the pandemic. Besides college students, lecturers and educational offices are also necessary to work from home to prevent and accelerate the decreasing Covid-19 pandemic (Kelana, 2020; Arifudin, 2020).

The Covid-19 pandemic policies and phenomenon that highly affect human life and quickly occur has forced higher education institutions to change their service work pattern from conventional to online-based (Ali, 2020; Almaiah et al., 2020). The government policy on establishing learning activities from home during the Covid-19 distresses the University. The information and communication technology facilities and human resources in the University are rather ready to conduct the online learning system. However, the University needs to gradually adopt this system (Kelana, 2020; Müller & Goldenberg, 2020). Lecturer are also demanded to be more creative in giving online materials, such as making learning videos of tutorials uploaded on YouTube and optimizing the use of Google Classroom, WhatsApp Group, and video conferencing applications (i.e. Zoom, Skype, Hangouts, and WebEx). Besides, the most point is communication, in which lecturers necessarily keep paying attention to their student development by ensuring their right to acquire education apart from the use of technology (Chen et al., 2020; Brown et al., 2020).

The use of technology of the online learning system during the Covid-19 gives both positive and negative impacts. The positive ones include giving students the freedom to express their unspoken ideas during face-to-face learning due to their shyness, reluctance, fear, or poor verbal communication. Furthermore, it aims to help students in isolated places who have difficulties in accessing the campus or also work in arranging their time, and to increase both lecturers' and students' creativities and independence in improving their qualities by continuously doing innovation to get new knowledge (Flack et al., 2020; Di-Pietro et al., 2020). However, the fact of different understanding levels indicates the negative one in students. Students who are diligent and easy to understand material materials can follow the online learning system effectively. Still, the ones who are not familiar with the system probably find it challenging to catch the materials and adapt the system. In fact, the obligation to study from home presents serious obstacles, especially students under previllaged families. They often complain about running out of the internet package. Moreover, the technology also possibly builds user attitude depending on an instant lifestyle (Rajhans et al., 2020; Subedi et al., 2020; Blazar & Kraft, 2017).

Considering the condition of education institutions during the Covid-19, many, particularly higher education institutions, realize that they need to work hard, think creatively, and adapt the

current situation by changing teaching and learning activities from conventional to e-learning (Sintema, 2020; Tran et al., 2020). The Covid-19 is a momentum for the education institutions to create innovations and leave the normative paradigm of real world to the virtual one by using the technology in every learning activity. In some discussions, many education observers claimed that the online learning suddenly implemented was ineffective and needed a huge cost for students. However, the Covid-19 forcefully discontinues face-to-face learning, and both students and lecturers have no choices than conducting the online system (Eyles et al., 2020; Reimers & Schleicher, 2020). Thus, it is important to conduct a study on determining factors affecting lecturer performance during the Covid-19.

Some relevant studies on measuring the lecturer performance have been conducted. For example, the study aims to analyze factors affecting the lecturer's performance in completing the teaching and learning process in the Midwife Program, Magelang for the academic year of 2005/2006 was conducted by Mundarti (2007). It was an observational study with the cross-sectional approach. The population was all full-time lecturers in the Midwife Program, Magelang. The bivariate analysis was conducted using the Chi Square test while the multivariate analysis used the logistic regression statistical test. The result of the bivariate analysis showed significant influences of lecturer age, education, motivation, satisfaction, perception on reward, and perception on supervision on lecturer performance in conducting teaching and learning process. Besides that, Exp(b) values of motivation toward performance are 25.67 and satisfaction toward performance as much as 11.21.

In addition, the influence of work motivation, relational capital, and structural capital on the lecturer performance in the Association of Indonesian Catholic Higher Education was investigated by Hermanto et al. (2019). It was quantitative and causal. It employed the questionnaire to obtain the research data, distributed to 62 lecturers. The data were analyzed using the multiple regression model. The result reflected that the work motivation, relational capital and structural capital affected the lecturer performance as much as 23%. In comparison, while the 76.8% influence was received. In addition, the influence of work motivation, relational capital, and structural capital on the lecturer performance in the Association of Indonesian Catholic Higher Education was investigated by Hermanto et al. (2019). It was quantitative and causal. It employed the questionnaire to obtain the research data, distributed other variables not included in the study. From three variables, work motivation significantly affect lecturer performance.

Moreover, the study conducted by Syarweni et al. (2019) found the dominant factors on the lecturer performance. It was to know which dominant factors between emotional intelligence, organization climate, and work satisfaction affected the lecturer performance in Politeknik Negeri Jakarta. It qualitatively used the Path Analysis Method. It obtained the data sample of as many as 77 respondents after giving the questionnaire to 325 lecturers of Politeknik Negeri Jakarta. The result indicated that emotional intelligence and work satisfaction became the dominant factors on lecturer performance, but the organization climate was insignificant.

Correspondingly, the study on teacher performance in junior high school was conducted by Hasbay and Altindag (2018). It investigated how factors in terms of wage, work environment, and management affected teacher performance. The data sample consisted of 103 respondents obtained through the survey. The data were evaluated and analyzed applying the factor, correlation, and regression analysis. The result showed that the teacher performance was chronologically affected by management, work environment, and wage. It implies that the wage is rather significant on the teacher performance. The good effort from the school management in building good communication and making the investment in developing teacher carrier and school facilities is essential. It also needs to create a comfortable and unstressful work environment.

Based on the explanation above, the study analyzed of factors affecting the lecturer's performance during the Covid-19 pandemic using the logistic regression model and parameter estimation measured with the genetic algorithm. It aimed to:

- Identify factors affecting the lecturer's performance, particularly lecturers at a University in Bogor, Indonesia.
- Determine the significance level of factors affecting the lecturer's performance partially and simultaneously.
- Determine the strength of the logistic regression model to analyze factors affecting the lecturer performance.
- Discuss the implementation of analyzed factors to improve the lecturer performance at a University in Bogor, Indonesia.

After conducting the literature review, the study suggested the gaps between the previous and present studies, as summarized in Table 1.

Table 1 shows the gaps between the previous and present studies as follows:

- The previous studies do not measure the lecturer's performance during the Covid-19 pandemic while the present study does.
- The previous studies do not include learning facility and technology literacy factors as included in the present study.

Table 1. Research Gap

| Authors | Titles | Methods | Factors (Variables) |
|----------------------------|--|---|--|
| Mundarti (2007) | Factors Affecting Lecturer Performance in Implementing Teaching and Learning Process in Magelang Midwifery Study Program, Semarang Health Polytechnic, Academic Year 2005/2006 | Crossectional, Chi Square test, logistic regression | Lecturer age, education, motivation, satisfaction, perception on reward, perception on supervision, and lecturer performance. |
| Hermanto et al. (2019) | Factors Affecting Performance Lecturer | Quantitative & causal, multiple regression model | Work motivation, relational capital, and structural capital as well as lecturer performance. |
| Syarweni et al. (2019) | Dominants Factors Analyzis on Lecturers Performance of State Polytechnic of Jakarta | Quantitative and Path Analysis | Emotional intelligence, organization climate, and work satisfaction as well as lecturer performance. |
| Hasbay and Altindag (2018) | Factors That Affect the Performance of Teachers Working in Secondary-Level Education | Factor, correlation, and regression analysis | Teacher wage, work environment, and management as well as teacher performance |
| This work | Analysis of Factors Affecting Lecturer Performance at a University during the Covid-19 Pandemic Using Logistic Regression and Genetic Algorithms | Logistic Regression and Genetic Algorithms | Lecturer age, education, motivation, satisfaction, perception on reward, perception on supervision, learning facility, and technology literacy as well as lecturer performance. |

The previous studies do not analyze the logistic regression model with the parameter estimation measured with the genetic algorithm approach, but the present one uses them.

The contribution of this research is to provide input and advice to the University, as consideration and evaluation to determine policies so that the performance of lecturers remains

adequate in carrying out the Tri Dharma of Higher Education activities, even in the Covid-19 pandemic situation.

2. Description of Measurement

This section describes the measurement of variables, both response variables and predictive variables. The description is done by referring to Mundarti. (2007), Akram (2010), and Mark (2015), are as follows:

Lecturer performance; is the success of respondents in completing their jobs with the process as the evaluation object, dealing with conducting the teaching and learning process that consists of planning, implementation, and evaluation. For the non-normal data distribution, the categorization uses the median value as many as 82.5. In addition, they include the low performance reflected $x < \text{median}$, and high performance referring to $x \geq \text{median}$ and measurement scale: nominal.

Lecturer age; is the respondent age in August, 2020 (the odd beginning semester in the academic year of 2020/2021) and measured in regard with the number of years, if the age ≥ 0.5 , it is rounded up, and if the age is < 0.5 , it is rounded down. For the non normal data distribution, the categorization uses the median value as much as 38. Thus, the categories consist of the young age to show $x < \text{median}$, old age to refer to $x \geq \text{median}$, and measurement scale: nominal.

Education; is the respondent's education level in terms of Doctoral Degree (S3)/ Master's Degree (S2) and Bachelor Degree (S1)/Bachelor Degree of Applied Science (DIV)/Associate Degree (DIII). The next analysis categorizes the subject into univariate descriptions, in terms of ordinal-scale variable and nominal-scale variable: Unqualified education: S1, DIV, DIII and qualified education: S2, S3, and measurement scale: nominal.

Work period; is the respondent work period since they become lecturers until the beginning odd semester in the academic year of 2020/2021 and measured based on the number of years, in which if the period ≥ 0.5 , the number is rounded up, if the period < 0.5 , it is rounded down. For the non-normal data distribution, the categorization uses the median value as much as 38. The categories include the short period for $x < \text{median}$, long period for $x \geq \text{median}$, and measurement scale: nominal.

Motivation; is the respondent's impulsion to conduct the teaching and learning process in terms of responsibility, student achievement, reward, and self-actualization in the teaching and learning process. For the normal data distribution, the descriptive analysis categorizes the subject into two as measured with a mean value of 42.93. The categories include the low motivation for $x < \text{mean}$, high motivation for $x \geq \text{mean}$, and measurement scale: nominal

Job satisfaction; is the compatibility of what is expected with what is experienced by respondents in conducting the teaching and learning process, includes the satisfaction in compiling syllabus and team teaching, compatibility between assigned subjects and expertise, number of assigned credits, available learning media, classroom area, opportunities to participate in seminars or trainings. For normal data distribution, the descriptive analysis categorizes the subject into 2 based on the mean value of as many as 35.68. The categories are the low job satisfaction for $x < \text{mean}$, high job satisfaction for $x \geq \text{mean}$, and the nominal measurement scale.

Perception on reward; is the respondent perception of all kinds of reward in terms of financial (salary, wage, incentive) as viewed from number, sufficiently, sense of justice, proportionality with the workload, and payday, and non-financial such as participating in seminars, workshops, training, and recreational programs. The descriptive analysis categorizes the subject into two for the normal data distribution, concerning the mean value as many as 59.07. The categories

reflect the perception of bad reward for $x < \text{mean}$ and good reward for $x \geq \text{mean}$ and measurement scale: nominal.

Perception on supervision; is the lecturer perception of the implementation of supervision activities (coaching, counseling, briefing, and control) from the department head on the teaching and learning process, including preparation of the teaching program, implementation of teaching program, problem-solving in teaching program implementation, evaluation on student learning outcomes, and evaluation on the teaching and learning process. The descriptive analysis categorizes the subject into two for the normal data distribution, regarding the mean value as many as 29.11. The categories are the bad perception of supervision for $x < \text{mean}$, and good perception on supervision for $x \geq \text{mean}$ and measurement scale: nominal.

Learning facility; is the tools needed in the learning process to achieve learning goals in terms of being well-conducted, organized, effective, and efficient. For the non-normal data distribution, the categorization uses the median value as many as 38. The categories include the bad learning facility for $x < \text{median}$, good learning facility for $x \geq \text{median}$, and measurement scale: nominal.

Technology literacy; is the lecturer's skill in operating the information and communication technology that could improve the institution and individual performance. Hence, ICT has a correlation to and direct impact on users and simultaneously improve their institution performance. For the non-normal data distribution, the categorization uses the median value as many as 56.66. Thus, the categories involve the low performance for $x < \text{median}$, high performance for $x \geq \text{median}$, and measurement scale: nominal.

The main objective is to analyze the factors that affect the performance of lecturers during the Covid-19 pandemic. Also, evaluate and implication the factors of age, education, motivation, satisfaction, perception of supervision, learning facilities, and technological literacy to lecturer performance.

3. Materials and Methods

In this section, the topics discussed include: research models, participants, data collection tools, data collection process, and data analysis.

3.1 Research Models

The research model here is intended to represent the relationship between various types of independent variables and the dependent variable. In this research, eight influential variables include: Age, Education, Motivation, Satisfaction, Perception of reward, Perception of supervision, learning facility, and technology literacy. In addition, there is one response variable, namely lecturer performance. The relationship between the eight influential variables and the response variable can be drawn a model research diagram as given in Figure 1.

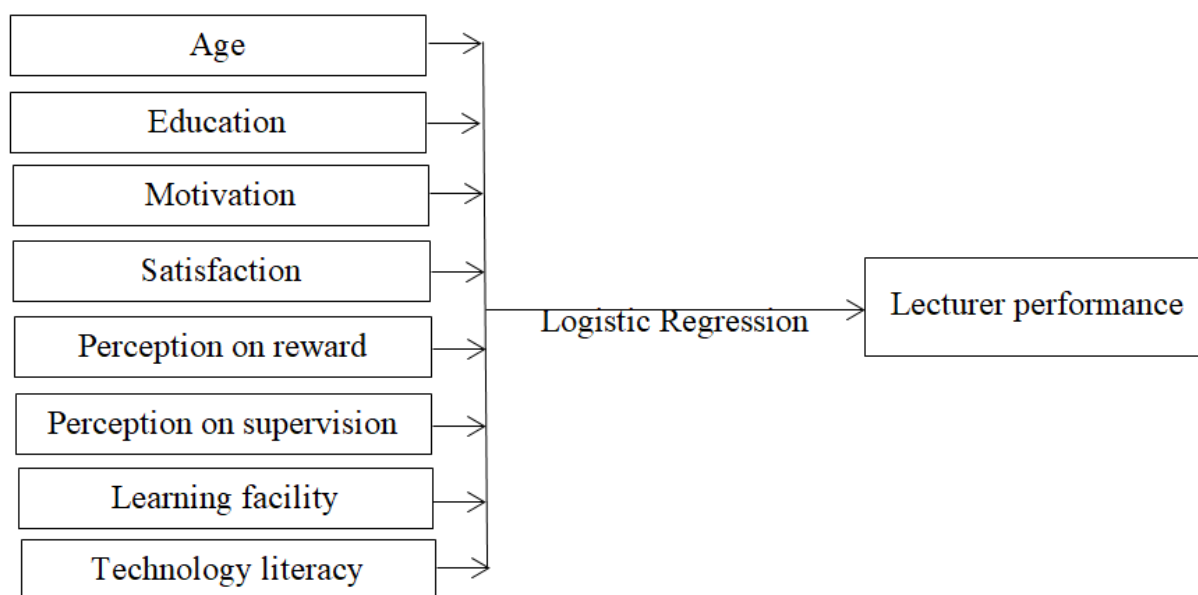


Figure 1. Relationship of Influential Variables with Response Variables

Figure 1, shows that eight variables simultaneously affect the response variable, following the logistic regression model.

3.2 Participant

Participants (Respondents) are parties who are the subject of a study and have an essential role in answering all the questions in a questionnaire. Respondents in this study as a population are all lecturers of PKN University, Bogor City, Indonesia. The sample in this study was taken from part of the lecturer population, conduct learning activities in the odd semester of the academic year 2020-2021. The number of samples is determined based on Roscoe's Theory, where the research is conducted with multivariate correlation analysis. Therefore, sample members are at least 10 times the number of variables studied (Sugiyono, 2015).

3.3 Data Collection Tools

Data collection tools, are tools that are needed or used to collect data. In this study, data were collected using a tool called a questionnaire. Questionnaire is a research instrument consisting of a series of questions that aim to collect information from respondents. The questionnaire can be considered as a written interview. It can be done face-to-face, over the phone, online or even by post.

During the questionnaire preparation, several steps were taken, including (a) Exploring the research questions to understand carefully the formulation of the questions from the research conducted. (b) Determine that the information to be collected can be converted into detailed questions or statements and compiled into a questionnaire. (c) Create a structured questionnaire, where the questions in the research questionnaire begin with the identity and characteristics of the research respondents. For the rest, researchers need to classify and arrange a series of questions to facilitate collecting data. (d) Make explanations or follow-up questions from the questionnaire, this is intended to dig deeper into the required information. (e) Conducting a test of the questionnaire is needed when it is desired to test how well the questionnaire has been made. Are the questions relevant to the characteristics of the respondents, or are there words that contain ambiguity in the questionnaire that can make respondents misunderstand?

Furthermore, the test of the validity and reliability of the instrument is one of the tests used to test the level of validity of the questionnaire items and how many the researchers' questionnaire measurement results can be trusted. The validity test of the research instrument can be declared

valid if each question item in the questionnaire can be used to reveal something that is measured by the questionnaire. Testing the instrument's validity in this study was conducted using Pearson's Product Moment analysis with a significance level of 0.05. Thus, high and low reliability are empirically indicated by a number called the reliability coefficient value. It is testing the instrument's reliability using the Alpha Cronbach formula because this research instrument is in the form of a questionnaire and a graded scale (Sugiyono, 2015).

3.4 Data Collection Process

Primary data collection through questionnaires before being distributed to respondents, the researcher first provides training to the research implementers so that the research objectives can be achieved. Then, after the executor clearly understands the instructions for filling out the questionnaire, then the researcher implements the research by giving questionnaires to the respondents to be filled out honestly. Because in the Covid-19 pandemic situation, where the mobility of people's movements is minimal, and all lecturers work from home, the distribution of questionnaires is done online. Likewise, explanations needed to make it easy for respondents to understand, can be done online or by telephone. After the questionnaire data was collected, the data was tabulated using the Excel 2010 software.

3.5 Data Analysis

3.5.1 Symbolization of variables and normality test

Factors assumed to have impacts on Lecturer performance $P(Y = j | x)$, included 8 (eight) variables, namely **Age** (X_1), **Education** (X_2), **Motivation** (X_3), **Satisfaction** (X_4), **Perception on reward** (X_5), **Perception on supervision** (X_6), **Learning facility** (X_7), and **Technology literacy** (X_8).

The study then conducted the normality test on all the data. Testing data normality was conducted due to the data value fluctuations from high to low of the independent variable. The high difference between values would result in a bias for the analysis so the lecturer's performance could not be expressed factually. The data normality test was conducted with the employment of statistic software of SPSS 17.0. After testing the data normality, the study conducted the estimation analysis on the logistic regression model.

This research was conducted based on the permission and approval of the Pakuan University ethics commission with a decree 69/Kep/SPs/Unpak/VI/2020. It was carried out following applicable regulations.

3.5.2 Logistic regression model

Logistic regression was part of the regression model possibly used to estimate the probability of an event, by matching the data on the logistic curve of the logit function. This method was the linear model generally used in the binomial regression. Similar to the regression model analysis in general, this method was conducted by involving some predictor variables in terms of numeric and category (Peng et al., 2002).

3.5.3 Multinomial logistic regression model

The data analysis in which the response variable was nominal was conducted using a method developed from the logistic regression model namely the nominal logistic regression model. Meanwhile, the analysis was conducted using the ordinal logistic regression model for the response variable of ordinal data (Pyke & Sheridan, 1993).

The multinomial logistic regression model is beneficial to describe the correlation of predictor variable (X) and response variable (polytomous). The nominal logistic regression model was frequently used when there was no sequence between response categories. One of the categories

was the reference category. The multinomial logistic regression model was generally represented in the following equation (Zewude & Ashine, 2016).

$$P(Y = j|x) = \pi_j(x) = \frac{\exp[g_j(x)]}{\sum_{k=0}^{r-1} \exp[g_k(x)]} \quad (1)$$

$$= \frac{\exp(\beta_{j0} + \beta_{j1}x_1 + \beta_{j2}x_2 + \dots + \beta_{jp}x_p)}{\sum_{k=0}^{r-1} \exp(\beta_{k0} + \beta_{k1}x_1 + \beta_{k2}x_2 + \dots + \beta_{kp}x_p)}$$

with $P(Y = j | x)$: conditional probability of response variable Y for the j (ordinal number) category on vector x , $j = 0, 1, \dots, r-1$; $\pi_j(x)$: logistic regression model of response variable Y for the j category; $g_j(x)$: logit model of response variable Y for the j category; x_m : value of the m (ordinal number) predictor variable, $m = 1, 2, 3, \dots, p$; β_{jm} : coefficient parameter of logistic regression model. Where vector $\tilde{\beta}_0 = 0$, so $g_0(x) = 0$; $\tilde{\beta}_0$: coefficient parameter of logit model for response variable to the 0 category $(\beta_{00}, \beta_{01}, \dots, \beta_{0p})$ (Ramosacaj et al., 2015; Korkmaz et al., 2012).

For the response variable with r category, the study formed a logit model equation in terms of $r-1$. Each equation formed the binary logistic regression that consisted of categories toward a preference, as represented in the following equation (2).

$$g_{r-1}(x) = \ln \frac{P(Y = r-1|x)}{P(Y = 0|x)} = \ln \left(\frac{\pi_{r-1}(x)}{\pi_0(x)} \right) = \beta_{(r-1)0} + \beta_{(r-1)1}x_1 + \dots + \beta_{(r-1)p}x_p \quad (2)$$

In general, the analysis steps in the multinomial logistic regression model included: (1) estimating coefficient parameters of the multinomial logistic regression; (2) testing the significance of coefficient parameters simultaneously to know the performance of multinomial logistic regression model estimators; (3) testing the significance of coefficient parameters partially to know which predictor variable is primarily affecting the response variable on the multinomial logistic regression; and (4) interpreting the ratio of trend value based on the multinomial logistic regression model estimators (Sukono et al., 2014; Rainey, 2016).

3.5.4 Coefficient parameter estimator

To estimate coefficient parameters of the logistic regression model, the expected values between response variables were not linear and contained different variation, so the estimator $\tilde{\beta}$ was possibly calculated using the Maximum Likelihood method. The function of conditional Likelihood for the data sample as many as n , the observation was indicated in the following equation.

$$l(B) = \prod_{i=1}^n \left[\pi_0(x_i)^{y_{0i}} \pi_1(x_i)^{y_{1i}} \pi_2(x_i)^{y_{2i}} \dots \pi_{r-1}(x_i)^{y_{(r-1)i}} \right]. \quad (3)$$

After that, if the left and right sides of equation (3) became the natural algorithm, the log Likelihood function was obtained as follows.

$$L(\beta) = \ln[l(\beta)] \quad (4)$$

$$L(\beta) = \ln \left[\prod_{i=1}^n \left[\pi_0(x_i)^{y_{0i}} \pi_1(x_i)^{y_{1i}} \pi_2(x_i)^{y_{2i}} \dots \pi_{r-1}(x_i)^{y_{(r-1)i}} \right] \right]$$

To find the estimator value of $\tilde{\beta}$ probably giving maximum value on equation (4). However, to determine the analytical solution of equation (4) produces a nonlinear system of equations that is difficult to determine the solution, so a numerical solution is required (Atkinson et al., 2005; Fotheringham et al., 2003). Therefore, the genetic algorithm is considered one of the most appropriate algorithms used to solve complex optimization problems, which is difficult for analytical methods (Minghua et al., 2017; Tomioka et al., 2007).

3.5.5 Genetic Algorithms

According to Czarnitzki & Doherr (2002), the genetic algorithm introduced by Goldberg in 1989 was a computational algorithm inspired by Darwin's evolution theory. This theory claimed that the continuity of an organism's life could be maintained by the process of reproduction, crossover, and mutation concerning the rule that the strong would win. It was then adapted into the computational algorithm to solve problems "naturally".

The solution obtained from the genetic algorithm was called as **chromosome**, and a set of chromosomes was **population**. Components of a chromosome were **genes**, and their values were in terms of number, binary, symbol, or character, depending on the problem. The chromosome was able to breed and known as **generations**. Each generation of chromosome was measured its achievement level of the solution value for objective functions, based on the measurement of **fitness**. The selection of chromosome maintained for the next generation was called as selection process (Hasheminia & Niaki, 2006).

A new chromosome was recognized as **offspring**, produced through crossbreeding between chromosomes in one generation, namely **crossover**. Many chromosomes in the population were determined through **crossover_rate**. A mechanism of characteristic changing in human beings due to natural factors is referred to as a **mutation**. The parameter of **mutation_rate** determined many genes experiencing mutation in the population. After some generation changes, chromosome values produced by genes would be obtained through the algorithm genetic with respect to the problem solving (Iquebal & Himadri, 2012).

In this study, the algorithm genetic was applied to determine logistic regression model estimators. These estimators were used to optimize the log Likelihood function regarding equation (6). The determination of maximum solution in equation (6), the study conducted the following steps (Murillo-Morera et al., 2017; Mardle et al., 2000).

- 1) Chromosome creation process; the estimated value was β_k ($k = 0, 1, \dots, K$), the used as parameter β_k and formed a gen chromosome. The parameter β_k had a domain of real number.
- 2) Initialization process; initialization gives the initial value to gen with random values adjusted to the determined limitation.
- 3) Chromosome evaluation process; this process determined β_k value on equation (6), indicating the objective function as chromosome was equation (6).
- 4) Chromosome selection process; selection was carried out by making chromosomes with small fitness value or high probability, most likely selected. Fitness function was $fitness = 1/(1 + objectif_function)$, added 1 on the divider to avoid null. Meanwhile, the probability value was measured using $P[i] = fitness[i] / total_fitness$. The selection process was probably conducted with random number generator and cumulative probability $C[k]$. Based on the cumulative probability values and random number generator R in the interval $[0, 1]$, the requirement is to choose chromosome 1 as a parent, unless choosing k chromosome $C[k-1] < R < C[k]$. These are conducted as much as possible concerning the population.

- 5) The crossover process is used one-cut-point, selecting one position in the parent chromosome conducted randomly, then gen changes. The chromosome as a parent was selected randomly, and the number of chromosomes experiencing crossover was affected by the **crossover_rate** parameter (ρc). For example, the probability value of crossover was determined as much as 25%. It was expected that one generation contained 50% chromosomes from one generation with crossover.
- 6) Mutation process; the number of chromosome experiencing the mutation process in a population was determined by **mutation_rate** parameter. The mutation process was taken place by changing randomly chosen genes, with new values obtained randomly. This process included, calculating the total length of gen existing in the population. The total length of gen was **total_gen = (number of genes in a chromosome)*(total population)**. To choose the position of mutating genes used the random number generator between 1 and the integers of **total_gen**. If the random number obtained was smaller the **mutation_rate** variable (ρm), choose the mutation position as sub-chromosome. After the mutation process was carried out, or one iteration of the genetic algorithm finished, it was called as generation. This process was conducted repetitively until the determined number of generation was gained, and the chromosome was obtained as the optimal solution of objective function.

3.5.6 Testing parameter estimator

1) Testing parameter estimator simultaneously

Testing coefficient parameter estimators simultaneously were conducted to test predictor variables' contribution on the response variable's multinomial logistic regression model estimators. The hypotheses included.

H_0 : $\beta_{j1} = \beta_{j2} = \dots = \beta_{jp} = 0$, there is no influence of a set of predictor variables on the response variable.

H_1 : there is minimally one $\beta_{jm} \neq 0$, indicating a predictor variable affecting the response variable, where $m = 1, 2, \dots, p$, with log Likelihood ratio as represented in the following equation.

$$G = -2 \ln \left[\frac{I_0}{I_k} \right]. \quad (5)$$

Test criterium was rejecting H_0 at the significance level α as the statistical vale $G > X^2_{(v;\alpha)}$ or $p - value < \alpha$. If H_0 was rejected, the predictor variables simultaneously affected the response variable (Sukono et al., 2014; Paterlini & Minerva, 2010).

2) Testing parameter estimator individually

Testing coefficient parameter estimators partially tested each predictor variable's contribution one after another using Wald test. The testing hypotheses were the followings.

H_0 : $\beta_{jm} = 0$, there is no influence of coefficient parameter estimator of the m predictor variable on the response variable of j category.

H_1 : $\beta_{jm} \neq 0$, there is influence of coefficient parameter estimator of the m predictor variable on the response variable of j category, where $j = 0, 1, 2, \dots, r-1$; $m = 1, 2, \dots, p$.

Testing was conducted using Wald test as the following equation.

$$W = \left[\frac{\hat{\beta}_{jm}}{Se(\hat{\beta}_{jm})} \right]^2. \quad (6)$$

Test criterium was rejecting H_0 for statistic $W > X^2_{(1;\alpha)}$ or $p\text{-value} < \alpha$. If H_0 was rejected, the coefficient parameter estimator $\hat{\beta}_{jm}$ significantly affected the response variable (Rijnhart et al., 2019; Sukono et al., 2014).

3) Hosmer & Lemeshow Test

Hosmer & Lemeshow test known as a test of logistic regression models were suitable for the data. Statistic test of Hosmer & Lemeshow was represented in the following equation.

$$\hat{C} = \sum_{k=1}^g \frac{(O_k - n_k \bar{\pi}_k)^2}{n_k \bar{\pi}_k (1 - \bar{\pi}_k)} \text{ or } P\text{-Value} = \Pr(\hat{C}), \quad (7)$$

with $O_k = \sum_{j=1}^{n_k} Y_j$ and $\bar{\pi}_k = \sum_{j=1}^{n_k} (m_j \bar{\pi}_j / n_k)$. The hypotheses are as follows:

H_0 : There is no difference between the results of observations with the logistic regression model used;

H_1 : There is a difference between the results of observations with the logistic regression model used.

Hosmer & Lemeshow was asymptosis on the Chi-Square distribution with degrees of freedom $df = (g - 2)$, with a general $g = 10$. Test criteria used were Reject a hypothesis of H_0 if statistic value $\hat{C} > \chi^2_{(1-\alpha)(g)}$, otherwise accepts the hypothesis of H_0 when $\hat{C} < \chi^2_{(1-\alpha)(g)}$ where α the significance level established the test (Sukono et al., 2014; Ng et al., 2008).

4) R-Square

According to Hosmer and Lemeshow, the determination value of R^2 in the logistic regression model analysis showed strong relationships between the predictor with response variables. Statistic of R^2 could be determined using the formula as follow:

$$R^2 = 1 - \exp \left[- \left(\frac{L^2}{N} \right) \right], \quad (8)$$

where the L was the value of the log likelihood of the model and N is the number of data. If the determination value of $R^2 \rightarrow 1$, then the relationship between the predictor variable with the response variable was strong. Conversely, if the determination value of $R^2 \rightarrow 0$, then relationship was weak (Sukono et al., 2014; Sidi et al., 2017).

4 Results and Discussion

The information about the research data has been explained in the sub-section 3.1. In this study, eight variables were analyzed, therefore based on Roscoe's Theory the minimum number of data samples is $n = 8 \times 10 = 80$. However, in the study the sample consisted of 150 respondents. They

were generally divided into two categories, namely $n_1 = 135$ or 90% for category 1 to refer to lecturers with high performance, and $n_0 = 15$ atau 10% for category 0, to indicate lecturers with low performance.

Furthermore, the validity test of the instrument used in this study was carried out by using Pearson's Product Moment analysis, with a significance level of 0.05 and a limit value of 0.3. The instrument validity test was carried out with the help software of SPSS version 17.0, and the results are given in Table 2.

Table 2. Instrument Validity Test Results

| Question Items | Correlation | Limit Value | Decision |
|----------------|-------------|-------------|----------|
| X_1 | 0.712 | 0.3 | Valid |
| X_2 | 0.827 | 0.3 | Valid |
| X_3 | 0.618 | 0.3 | Valid |
| X_4 | 0.735 | 0.3 | Valid |
| X_5 | 0.515 | 0.3 | Valid |
| X_6 | 0.816 | 0.3 | Valid |
| X_7 | 0.565 | 0.3 | Valid |
| X_8 | 0.554 | 0.3 | Valid |

Table 2 shows the instrument validity test results using the Pearson Correlation method; it was found that the correlation values of each question item were greater than the limit value. Thus, a total of eight question items are all valid to use.

Instrument reliability testing was carried out using the Cronbach Alpha method at a significance level of 0.05 and a limit value of 0.7. The instrument reliability test was carried out with the help of SPSS-version-17.0 software, and the results are given in Table 3.

Table 3. Instrument Reliability Test Results

| Question Items | Cronbach Alpha | Limit Value | Decision |
|----------------|----------------|-------------|----------|
| X_1 | 0.782 | 0.7 | Reliable |
| X_2 | 0.757 | 0.7 | Reliable |
| X_3 | 0.796 | 0.7 | Reliable |
| X_4 | 0.788 | 0.7 | Reliable |
| X_5 | 0.823 | 0.7 | Reliable |
| X_6 | 0.765 | 0.7 | Reliable |
| X_7 | 0.812 | 0.7 | Reliable |
| X_8 | 0.824 | 0.7 | Reliable |

Table 3 displays the results of the instrument reliability test show that each question item produces a Cronbach Alpha value greater than the limit value. Therefore, the eight question items used are reliable to use.

Next step, to conduct the logistic regression model analysis, the study needs to test the data normality. It aims to ensure that the data distribution is normal. It deploys the software of SPSS version 17.0. After ensuring the data distribution is normal, the binary logistic model parameters are estimated.

4.1 Results

In this section, the study estimates the binary logistic regression parameters to obtain the coefficient parameter estimator $\hat{\beta} = (\hat{\beta}_0, \hat{\beta}_1, \dots, \hat{\beta}_8)$ which gives the maximum value of log Likelihood function in equation (4). The estimation process was carried out using the genetic algorithm approach regarding the steps discussed in sub-section 3.3 and the employment of Matlab 7.0 software (Öztürkler & Altan, 2008; Pan et al., 1995). The result of each estimator's coefficient parameters, error standard, and ratio values is reflected in Table 4.

The next is testing the significance of the overall influence of predictor variables toward the response variable $\pi(X)$. The test determines the null hypothesis in terms of $H_0 : \hat{\beta}_0 = \hat{\beta}_1 = \dots = \hat{\beta}_8 = 0$, against the alternative one with $H_1 : \exists \hat{\beta}_0 \neq \hat{\beta}_1 \neq \dots \neq \hat{\beta}_k \neq 0$ ($k=0,1,\dots,8$). The testing process uses the log Likelihood ratio in equation (5). The result is reflected in Table 4.

The calculation with the employment of SPSS software version 17.0 results in the log Likelihood ratio statistic $\hat{G} = -45.722$. This log Likelihood ratio statistic \hat{G} is asymptotically follow the chi-square distribution (χ^2) in which the degree of freedom is $df = 8$. Suppose the significance level is determined as many as $\alpha = 0.05$, it obtained the statistical value $\chi^2_{(1-0.05)(8)} = 2.7326$ regarding the chi-square table. It is clear that the statistical value is $\hat{G} > \chi^2_{(1-0.05)(8)}$, resulting in that H_0 is rejected. It is suggested that the estimator $\hat{\beta} = (\hat{\beta}_0, \hat{\beta}_1, \dots, \hat{\beta}_8)$ of predictor variables simultaneously affect the response variable $\pi(X)$.

Table 4. Parameter and Standard Error Estimators

| Coefficient Parameter of Variables (X_i) | Estimator of Parameter ($\hat{\beta}_i$) | Error Standard $SE(\hat{\beta}_i)$ | Ratio (\hat{Z}) $\frac{\hat{\beta}_i}{SE(\hat{\beta}_i)}$ | Significance |
|--|--|------------------------------------|---|-----------------|
| Constant | -2.680 | 0.649 | -4.130 | Significance |
| Age (X_1) | -1.043 | 3.683 | -0.283 | Significance |
| Education (X_2) | 0.776 | 0.786 | 0.987 | Significance |
| Motivation (X_3) | 0.765 | 0.654 | 1.170 | Significance |
| Satisfaction (X_4) | 0.564 | 2.072 | 0.272 | Significance |
| Perception on reward (X_5) | 0.099 | 0.523 | 0.189 | No Significance |
| Perception on supervision (X_6) | 0.854 | 3.106 | 0.275 | Significance |

| | | | | |
|-------------------------------|-------|-------|-------|--------------|
| Learning facility (X_7) | 0.928 | 0.556 | 1.670 | Significance |
| Technology literacy (X_8) | 2.054 | 1.769 | 1.161 | Significance |

Log Likelihood Statistic = -45.722

The next is partially testing the coefficient parameter estimators to measure each predictor variable's significance on the response variable $\pi(X)$. The test determines the null hypothesis in terms of $H_0 : \hat{\beta}_k = 0$ against the alternative one namely $H_1 : \hat{\beta}_k \neq 0$ ($k=0,1,\dots,8$). The test uses the Z -ratio of statistics or Wald test with reference to equation (6). The result of \hat{Z} ratio is shown in Table 4. The \hat{Z} ratio reflects the standard normal distribution. If the significance level is in $\alpha = 0.05$, considering the standard normal distribution table, the test obtains the \hat{Z} ratio of $Z_{\frac{1}{2}(0.05)} = -0.27$ and $Z_{\frac{1}{2}(1-0.05)} = 0.27$. Besides, Table 4 shows that the \hat{Z} ratio for the estimator $\hat{\beta}_5$ is in the interval $-0.27 \leq \hat{Z} \leq 0.27$, so the H_0 is accepted. This means that the coefficient $\hat{\beta}_5$ is not significant, or the predictor variable X_5 insignificantly affect the response variable $\pi(X)$.

While the coefficient $\hat{\beta}_5$ is not significant, this coefficient is ignored (taken out) from the estimated logistic regression model. As a consequence, there is a need to conduct the re-estimation without the predictor variable X_5 . It is conducted using the genetic algorithm approach (Rizzo & Battaglia, 2018). The result is as shown in Table 5.

Table 5. Parameter Estimator and Standard Error of Re-Estimation

| Coefficient Parameter of Variables (X_i) | Estimator of Parameter ($\hat{\beta}_i$) | Error Standard $SE(\hat{\beta}_i)$ | Ratio (\hat{Z}) $\frac{\hat{\beta}_i}{SE(\hat{\beta}_i)}$ | Significance |
|--|--|------------------------------------|---|--------------|
| Constant | -2.780 | 0.637 | -4.364 | Significance |
| Age (X_1) | -1.133 | 3.485 | -0.325 | Significance |
| Education (X_2) | 0.785 | 0.685 | 1.145 | Significance |
| Motivation (X_3) | 0.768 | 0.654 | 1.175 | Significance |
| Satisfaction (X_4) | 0.654 | 2.172 | 0.301 | Significance |
| Perception on supervision (X_6) | 0.864 | 3.126 | 0.276 | Significance |
| Learning facility (X_7) | 0.948 | 0.568 | 1.669 | Significance |
| Technology literacy (X_8) | 2.254 | 1.765 | 1.277 | Significance |

Log Likelihood = -37.832

Conducting the log Likelihood ratio and Wald tests examines the significance of coefficient parameter estimator results of the re-estimation. The tests are similar to the previous ones and show that the estimators $\hat{\beta}_1, \hat{\beta}_2, \hat{\beta}_3, \hat{\beta}_4, \hat{\beta}_6, \hat{\beta}_7,$ and $\hat{\beta}_8$ are significant, as reflected in Table 5. The next step is conducting Hosmer & Lemeshow test.

Hosmer & Lemeshow test on the coefficient parameter estimators of the re-estimation result is conducted to analyze the compatibility level of the logistic regression model and real data obtained from the study. This test determines the following hypotheses.

H_0 : There is no difference between the observed results with logistic regression model estimators obtained;

H_1 : There is a difference between the observed results with logistic regression model estimators obtained.

Hosmer & Lemeshow test is with reference to equation (7). It is calculated based on the *P_Value*, with the testing criterium of rejecting H_0 if the *P_Value* is smaller than the significance level determined. In this test, the *P_Value* is 0.392. As the significance level is determined as $\alpha = 0.05$, it is clear that if the *P_Value* is higher than the significance level. Henceforth, H_0 is accepted, referring to “no differences between the observation and estimators of the logistic regression model”.

The next step is measuring the correlation between the predictor variables and the response variable. It is based on the statistical value R^2 , calculated using equation (8). The linear regression estimator equation results in $R^2 = 0.990$, indicating that the predictor variables: **Age** (X_1), **Education** (X_2), **Motivation** (X_3), **Satisfaction** (X_4), **Perception on Supervision** (X_6), **Learning facility** (X_7), and **Technology literacy** (X_8), have the strong correlation with the response variable $\pi(X)$. In other words, the predictor variables of 0.990 can explain the response variable, and other variables explain 0.010. Based on the re-estimation analysis as presented in Table 5 and referring to equation (2), the logistic regression model estimator has the following equation.

$$\hat{g}_{r-1} = \ln \left(\frac{\pi_{r-1}(x)}{\pi_0} \right) = -2.780 - 1.133X_1 + 0.785X_2 + 0.768X_3 + 0.654X_4 + 0.864X_6 + 0.948X_7 + 2.254X_8. \quad (9)$$

The logistic regression estimator equation (9) represents how each predictor variable affects the response variable (lecturer performance), in conducting *Tri Dharma of Higher Education* in the University during the Covid-19 and how huge their influence is.

4.2 Discussion

Since the spread of Covid-19, all academic activities in the University have changed into the online learning system. The shift from face-to-face learning to online learning is supposed to be effective and efficient and does not ignore each learning element's necessity on the campus (Rapanta et al., 2020). However, many civitas academics complain about this online system due to obstacles in implementing it (Alkharang, 2014). They are related to signal, internet data package, and laptop. Besides, the online learning system creates difficulties for students on understanding the materials. Many lecturers only focus on giving assignments and do not complement it with giving materials and conducting discussions (García-González et al., 2020; Naseer, 2010). Other obstacles are the diversity of the e-learning system used by some lecturers and the skill of educational stakeholders in using e-learning (Means et al., 2009). These obstacles affect the lecturer's performance in conducting *Tri Dharma of Higher Education*. Therefore, the head of the University necessarily conducts the strategic efforts and policies, but the University needs to decide based on the priority scale that effectively improves the lecturer performance.

Regarding the result represented in Table 1, the estimator $\hat{\beta}_5$ is not significant, indicating that the predictor variable X_5 insignificantly affect the response variable $\pi(X)$. This indicates that the policy of increasing lecturer wage is ineffective in improving the lecturer performance since the lecturer benefit is considered good. Moreover, based on Table 5 and equation (9), the estimator $\hat{\beta}_1 = -1.133$ referring to that the predictor variable X_1 is significant on the response variable $\pi(X)$. This implies that assigning younger lecturers in conducting online learning activities effectively improves the lecturer performance (Abbas et al., 2019). It is because they quickly adapt the development of technology. Meanwhile, the older ones are generally suitable to conduct researches and publications as they have more academic experiences.

Another factors necessarily becoming the priority in improving the lecturer performance during the Covid-19 are learning facility and technology literacy. With reference to Table 5 and equation (9), the study obtained the estimators $\hat{\beta}_7 = 0.948$ and $\hat{\beta}_8 = 2.254$ with the ratios of significance level as many as 1.669 and 1.277. These results are considered as the two highest number compared to other factors. It indicates that **Learning facility and Technology literacy** are related to each other and urgently need to be followed-up by some policies and improvements due to its impact on the lecturer performance in conducting the online learning activities. Moreover, the head of University must be brave to make an investment on the procurement of facilities directly supporting online learning activities, for instance providing high spec computers and buying online learning software licenses, to simplify lecturers in conducting online learning activities. Besides, the head of University also needs to give various trainings to improve the lecturer technology literacy, such as training on using online learning softwares, compiling learning materials based on online applications, and so forth (Rivkin et al., 2005; Yunus et al., 2011).

However, other factors in terms of **education, motivation, satisfaction, and perception on supervision** also need to become the head of University's concern, but **Learning facility and Technology literacy** are considered as the priority and urgent to be improved for achieving the improvement of lecturer performance during the Covid-19 pandemic

5. Conclusion

The study analyzed factors affecting the lecturer performance in the University during the Covid-19 pandemic, using the logistic regression model and coefficient parameters with the genetic algorithm. The study concludes that age, education, motivation, satisfaction, perception of supervision, learning facility, and technology literacy significantly affect the lecturer's performance. The logistic regression model estimator results in the statistical value of the coefficient of determination as many as 0.990, which is categorized as 'very strong'. The result indicates that learning facility and technology literacy factors need to be mainly improved, so the lecturer performance during the Covid-19 pandemic also shows the improvement.

In this study, lecturer performance only considers 8 (eight) variables, namely: Age, Education, Motivation, Satisfaction, Perception of reward, Perception of supervision, learning facility, and Technology literacy, which may need to be refined again. For future research, it is deemed necessary to consider other variables, such as organizational commitment, professional commitment, employment status, etc.

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