Mathematical Mastery in the Digital Age: Insights from Student Perspectives and Course Performance

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Abstract. This survey research aimed to identify the factors that influence student learning outcomes in the online Fundamental Mathematics I course at Del Institute of Technology during the odd semester of the 2022/2023 academic year. The study used a quantitative approach and a questionnaire as a data collection instrument. The participants were active students who took the course, and the data analysis used descriptive statistics and multinomial logistic regression. The findings revealed that internal factors, including interest and motivation, health, learning method, intelligence, and talent, significantly influenced student learning outcomes. Additionally, external factors such as campus and surroundings matter were also significant predictors of student achievement. The results of this study have important implications for educators and policymakers in designing effective online learning strategies that consider both internal and external factors to enhance student learning outcomes.

Keywords: Factors · Learning Outcomes · Surveys · Feasibility Test · Descriptive Statistics · Quantitative · Multinomial Logistic Regression

1 Introduction

In March 2020, the SARS-CoV-2 (COVID-19) coronavirus epidemic was declared a global pandemic by the World Health Organization.This kind of situation caused employees from different companies and labor sectors to work from home all over the world [1, 2]. Not to mention that the education sector has been obligated to provide online courses, which means that students must take those courses from a different location than their regular classrooms at schools or campuses. Almost all sectors of activity have been affected by COVID-19, but teaching and learning are significantly affected. Higher education institutions' reactions to the epidemic often fall into three categories [3]: retaining in-class teaching with social distance, developing hybrid models (blended learning, limiting the number of students on campus), or switching to online instruction.

One type of education that happens online is e - learning. E - learning is one sort of distant learning that takes place outside of the traditional classroom. Compared to traditional teaching techniques, it increases students' access to education because they

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can complete their coursework whenever they choose, anywhere, and with the option of part- or full-time study. [4]. The standard learning method can sometimes make pupils feel bored, which has an impact on their learning outcomes. Conventional learning cannot be done as usual during the COVID-19 epidemic. Interactive activities like teacher-student interaction, student-student interaction, student-content interaction, and student-technology interaction are extensively taken into account when teaching and learning online. Students who took the hybrid course in which formative assessment was employed to assess student learning results. Through the use of a learning management system, many learning activities are combined to carry it [5]. Online learning, as the name suggests, is a situation in which communication between the teacher and the pupils takes place through the internet. The teachers may also be in the same building as the students, and the students have been trained and taught via online technologies [6]. Many pupils despise mathematics because they find it to be very challenging. It seems to reason that students' motivation to learn mathematics will decline with online learning.

Mathematics learning is one of the learning way to develop critical, logical, creative, and collaborative thinking skills, where these abilities are indispensable in modern life [7]. Mathematics learning is important to the development of the abilities of each student to become a qualified human resource [8]. Students' ability to understand mathematics must be developed if they are to become aware of their environment and capable of solving difficulties that arise there.

As a part of Indonesia's educational system, the professors are burdened by the nation's students' poor performance on the global stage. The role of the lecturer is to provide, demonstrate, guide, and motivate students to interact with various learning resources. Lecturers must develop into more than just speakers of information to students; they must also assist in their skill-building. For the learning process to develop and draw student interest and motivation, a lecturer must be able to design active, inventive, creative, effective, and engaging learning.

The attainment of the effectiveness of the learning process, which will directly affect learning outcomes, is supported by learning interest, which is a crucial component. Interest is the desire to perform an action or activity without being asked. Interest is essentially the acceptance of a connection between something outside of oneself and something within of them. The interest increases with the strength or proximity of the relationship. The efficacy of the learning process is also influenced by motivation. A student can be encouraged both internally and externally through motivation, which has a number of signs or supporting components. These characteristics include the need to learn and be encouraged, ambitions and aspirations for the future, appreciation of learning, and a supportive atmosphere for learning.

Learning interest is a student's desire to participate in their education voluntarily [9]. High student motivation to participate in learning and increase student accomplishment comes from a source of interest in the subject matter [10]. The correlation between a student's level of achievement and their level of interest in their studies promotes motivation to do well in school [11]. The definition of interest in learning is a propensity toward something because it is profitable. When people see that something is profitable, then they will sense the interest because it can bring satisfaction [12]. Considering the previous experts' perspectives, it can be said that interest is a person's sense of curiosity, attention, and desire to do something.

These new conditions may affect students' safety, comfort, health, and academic performance, according to the research findings described above [13–15], and [16]. Similar to how exposure to various noise, temperature, and lighting levels may distract and bother them [13, 14], and [15]. In addition to these conditions, students must interact with their new study station, which includes a computer, mouse, chair, table or desk, and electrical outlets. If this equipment is not designed with an ergonomic approach, it may force certain body parts into awkward postures. These uncomfortable positions can cause physical aches and pains (in the back, neck, legs, hands, fingers, and wrists), which could develop into MSDs [17]. Online learning can lead to increased mental strain or intellectual weariness in terms of psychosocial aspects [16].

Based on the explanation above, learning outcomes are influenced by several factors. One of them is internal factors including interest and motivation, health, way of learning, intelligence and talent. Based on this, the writer wants to find out the internal factors that influence the learning outcomes of elementary I students at Del Institute of Technology and analyze how these factors can affect their learning achievements. Therefore, this research is entitled "Analysis of Internal Factors Affecting Student Learning Outcomes in Fundamental Mathematics I with Multinomial Logistic Regression".

2 Literature Review

2.1 Internal Factors Influencing Learning Eagerness

At the higher level education, students are more required to be able to learn without being completely dependent on lecturers. But each individual has a different tendency of independence. Both internal (from within the person) and external (from the environment) variables might have an impact [4]. Based on El-Soud's et al. in their journal [4], internal factors are divided into several items, namely: interest and motivation, health, way of learning, and intelligence and talent.

2.2 Learning Outcomes

The outcomes of student learning serve as an assessment criterion for the learner's academic goals. Summative and formative assessments are frequently used to evaluate student achievement, according to Nguyen [5]. The first estimated results were determined by test results or evaluations at the end of the course, whilst the second estimated outcomes were established through student learning while taking a variety of factors into consideration.

Specifically on this study, the focused evaluation is the summative assessment which is held at the half of the semester or often called as the midterm test. Summative assessment is the most suitable approach of acquiring student awareness, according to El-Shoud et al. [4], even though formative assessment is an excellent means to see student performances or achievement.

3 Methodology

3.1 Data

In this study, the population were all students of the Del Institute of Technology who took Fundamental Math I course which included 209 people. The data consists of questionnaires and midterm exam scores. There are 15 questions in the survey, and they cover every internal component that affects students' learning outcomes. The midterm results for Matematika Dasar I serve as the dependent variable (Y), and they are divided into three categories: low, medium, and high. The independent variable (X) is a questionnaire containing internal factors that influence learning outcomes, namely interest & motivation, health, learning methods, and intelligence & talent.

Variables used in this method are by following:

a. The response variables are categorical, namely the midterm exam scores consist of three categories (Low = 1, Medium = 2, High = 3).
b. Predictor variables are presented in Table 1.

Table 1. Predictor Variables.

Predictors	Description	Category	
$X_1, X_2, X_3, X_4, X_5, X_6$	Questions regarding interest and motivation	Never	1
		Sometimes	2
		Often	3
		Usually	4
X_7, X_8	Questions regarding health	Never	1
		Sometimes	2
		Often	3
		Usually	4
$X_9, X_{10}, X_{11}, X_{12}, X_{13}, X_{14}$	Questions regarding learning method	Never	1
		Sometimes	2
		Often	3
		Usually	4
X_{15}	Questions regarding intelligence and talent	Never	1
		Sometimes	2
		Often	3
		Usually	4

3.2 Logistic Regression

In many ways, when the target variable is categorized, logistic regression is the obvious complement to standard linear regression [18]. For a target (dependent) variable Y with two class and predictor (independent) variable X, let $g(x) = \Pr(X = x) = 1 - \Pr(X = x)$, the logistic regression model has a linear from Logit with probability as follows:

$$Logit\big[g(x)\big] = log\left(\frac{g(x)}{1 - g(x)}\right) = \alpha + \beta x,\ \ where\ the\ odds = \frac{g(x)}{1 - g(x)} \quad (1)$$

The logit has a form of linear approximation, and logit is equaled with the logarithm of the odds. The parameter β is the rate of increase or decrease of the S-shaped curve of $g(x)$.

3.3 Multinomial Logistic Regression

A data analysis technique called multinomial logistic regression expands the use of logistic regression to issues involving many classes [10]. Given a collection of independent variables, the model is frequently used to forecast the probabilities of the various outcomes of a categorically distributed dependent variable (which may be real-valued, binary-valued, categorical-valued, etc.)The aim of this method is to find the relationship between the response variables (denoted as y) which is multinomial. The hypothesis consist of:

H_0: The model is suitable or to define that there is no difference between the observed results and the possible prediction results of the model

H_1: The model is not suitable or to define that there is a difference between the observed results and the possible prediction results of the model

Multiple predictor variables can be included in a logistic regression model [19]. Let u define the number of predictors for a binary response Y by $x_1, x_2, x_3, \ldots, x_u$. The model for log odds as follows:

$$Logit[\Pr(Y = 1)] = \alpha + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \ldots + \beta_u x_u \quad (2)$$

and the alternative formula, directly specifying $h(x)$ is

$$h(x) = \frac{\exp\left(\alpha + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \ldots + \beta_u x_u\right)}{1 - \exp\left(\alpha + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \ldots + \beta_u x_u\right)} \quad (3)$$

The parameter β_i, for $1 < i \leq u$ and $1 < j \leq u$ and $i \neq j$, refers to the effect of x_i on the log odds that $Y = 1$, controlling other x_j, for instance, $\exp(\beta_i)$ is the multiplicative effect on the odds of a one-unit increase x_i, at fixed level of other x_j.

If we have n independent observations with u-predictor variables, and the target variable has q categories, to build the logits in the multinomial case, one of the categories must be considered as the base level and all the logits' functions are constructed relative to it. There are no conditions to turn the category into the base level, so it can be chosen randomly, in such a way that it turns category z as the base level. Due to the fact that there is no order, it is possible that any category could be labeled z. Let H_j denote the multinomial probability of observation for the j^{th} category, to find the relationship between this probability and the u-predictor variables, $X_1, X_2, X_3, \ldots, X_u$, the multinomial logistic regression model is:

$$\log\left[\frac{H_j(x_i)}{H_z(x_i)}\right] = \alpha_{01} + \beta_{1j}x_{1i} + \beta_{2j}x_{2i} + \ldots + \beta_{uj}x_{ui} \tag{4}$$

where $j = 1, 2, \ldots, z-1$ and $i = 1, 2, \ldots, n$. Since all the H 's adds to unity this reduces to

$$\log\log\left(H_j(x_i)\right) = \frac{\exp\left(\alpha_{01} + \beta_{1j}x_{1i} + \beta_{2j}x_{2i} + \ldots + \beta_{uj}x_{ui}\right)}{1 + \sum_{j=1}^{z-1}\left(\alpha_{01} + \beta_{1j}x_{1i} + \beta_{2j}x_{2i} + \ldots + \beta_{uj}x_{ui}\right)} \tag{5}$$

for $j = 1, 2, \ldots, z - 1$. The model parameters are determined by the method of multinomial linear.

4 Result and Discussion

4.1 Respondent's Characteristics

An evaluation of the respondents' characteristics was done to ascertain their general health, and the results can be utilized to help choose the responses that will be used in multinomial logistic regression modeling. The determination of the response variable is obtained by looking at the results of the descriptive statistical analysis using the pie chart shown in Fig. 1.

Figure 1 shows that the highest category of learning outcomes is the medium category, while the low and high categories are almost the same.

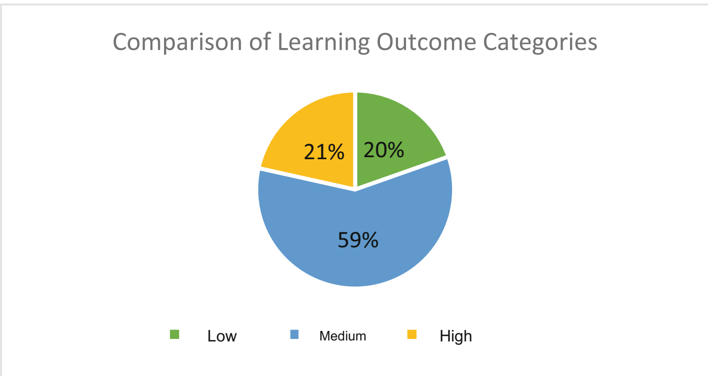

Fig. 1. Comparison of Learning Outcome Categories

Table 2. Simultaneous Test Multinomial Logistic Regression Model

G	Sig
265,614	0,000

4.2 Modeling Factors Influencing Learning Outcomes

In this modeling, the relationship between the response variables will be sought, namely the learning outcomes category and the predictor variables contained in Table 1. Multinomial logistic regression modeling is done by conducting simultaneous tests, partial tests and model suitability tests.

Simultaneous Test
Simultaneous tests were carried out to determine whether the model was appropriate (significant) and to examine the overall increase in the β coefficient with the following hypothesis.

H_0: $\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7 = \beta_8 = \beta_9 = \beta_{10} = \beta_{11} = \beta_{12} = \beta_{13} = \beta_{14} = \beta_{15} = 0$
H_1: at least there is one $\beta_j \neq 0$ where $j = 1, 2, \ldots, 15$j = 1, 2, … , 15.

The statistical test used in the simultaneous test is the G test or the likelihood ratio test. By carrying out simultaneous testing using SPSS software, the values listed in Table 2.

Based on the output from SPSS on Table 2 which obtained *p-value* 0,000 $< \alpha =$ 0,10 then H_0 is rejected. It means that there is at least one predictor variable that influences learning outcome categories.

Individual Test
To establish the parameters' relevance for the response variance, individual tests were run.In this test, we want to know the predictor variables that influence the learning outcomes category. The parameter significance test uses the Wald test. The hypothesis tested is as follows:

H_0: $\beta_j = 0$ ($j = 1, 2, \ldots, 15$).
(jth predictor variable has no influence to the learning outcomes category)
H_1: $\beta_j \neq 0$ ($j = 1, 2, \ldots, 15$).
(jth predictor variable has influences to the learning outcomes category)

By conducting individual tests using SPSS software on the response variable with each predictor variable, the values listed in Table 3.

Table 3. Individual Test of Multinomial Logistic Regression Model

Prediktor	**Wald**	**Sig**	**Prediktor**	**Wald**	**Sig**
Logit 1 (Low)			**Logit 2 (Medium)**		
Intercept	,000	,984	Intercept	,508	,476
[X1 = 2,00]	1,079	,299	[X1 = 2,00]	,831	,362
[X1 = 3,00]	,449	,503	[X1 = 3,00]	,256	,613
[X1 = 4,00]	.	.	[X1 = 4,00]	.	.
[X2 = 1,00]	.	.	[X2 = 1,00]	,000	1,000
[X2 = 2,00]	,000	,999	[X2 = 2,00]	,000	,999
[X2 = 3,00]	2,826	,093	[X2 = 3,00]	,172	,678
[X2 = 4,00]	.	.	[X2 = 4,00]	.	.
[X3 = 1,00]	,000	,992	[X3 = 1,00]	,000	,992
[X3 = 2,00]	,051	,822	[X3 = 2,00]	2,029	,154
[X3 = 3,00]	,798	,372	[X3 = 3,00]	2,309	,129
[X3 = 4,00]	.	.	[X3 = 4,00]	.	.
[X4 = 1,00]	,000	,997	[X4 = 1,00]	,000	,998
[X4 = 2,00]	,801	,371	[X4 = 2,00]	8,541	,003
[X4 = 3,00]	,462	,497	[X4 = 3,00]	10,955	,001
[X4 = 4,00]	.	.	[X4 = 4,00]	.	.
[X5 = 2,00]	,149	,699	[X5 = 2,00]	,006	,937
[X5 = 3,00]	,054	,817	[X5 = 3,00]	1,300	,254
[X5 = 4,00]	.	.	[X5 = 4,00]	.	.
[X6 = 2,00]	,000	,999	[X6 = 2,00]	,000	,999
[X6 = 3,00]	,240	,624	[X6 = 3,00]	,087	,767
[X6 = 4,00]	.	.	[X6 = 4,00]	.	.
[X7 = 2,00]	1,495	,221	[X7 = 2,00]	,341	,559
[X7 = 3,00]	,006	,937	[X7 = 3,00]	,378	,539
[X7 = 4,00]	.	.	[X7 = 4,00]	.	.
[X8 = 1,00]	,000	,999	[X8 = 1,00]	,000	1,000
[X8 = 2,00]	,422	,516	[X8 = 2,00]	,572	,449
[X8 = 3,00]	1,149	,284	[X8 = 3,00]	3,416	,065
[X8 = 4,00]	.	.	[X8 = 4,00]	.	.
[X9 = 1,00]	,000	,999	[X9 = 1,00]	,000	,988
[X9 = 2,00]	,000	,986	[X9 = 2,00]	,123	,726

(*continued*)

Table 3. (*continued*)

Prediktor	Wald	Sig	Prediktor	Wald	Sig
Logit 1 (Low)			**Logit 2 (Medium)**		
[X9 = 3,00]	,000	,985	[X9 = 3,00]	,165	,685
[X9 = 4,00]	.	.	[X9 = 4,00]	.	.
[X10 = 1,00]	1,359	,244	[X10 = 1,00]	1,314	,252
[X10 = 2,00]	1,136	,287	[X10 = 2,00]	,994	,319
[X10 = 3,00]	3,683	,055	[X10 = 3,00]	2,836	,092
[X10 = 4,00]	.	.	[X10 = 4,00]	.	.
[X11 = 1,00]	,000	,999	[X11 = 1,00]	,000	,999
[X11 = 2,00]	4,048	,044	[X11 = 2,00]	,391	,532
[X11 = 3,00]	,005	,946	[X11 = 3,00]	3,358	,067
[X11 = 4,00]	.	.	[X11 = 4,00]	.	.
[X12 = 2,00]	6,720	,010	[X12 = 2,00]	2,619	,106
[X12 = 3,00]	1,691	,194	[X12 = 3,00]	1,557	,212
[X12 = 4,00]	.	.	[X12 = 4,00]	.	.
[X13 = 1,00]	,000	,999	[X13 = 1,00]	,000	,999
[X13 = 2,00]	,671	,413	[X13 = 2,00]	,001	,976
[X13 = 3,00]	,000	,985	[X13 = 3,00]	5,511	,019
[X13 = 4,00]	.	.	[X13 = 4,00]	.	.
[X14 = 1,00]	,000	,987	[X14 = 1,00]	,000	,987
[X14 = 2,00]	1,003	,317	[X14 = 2,00]	2,812	,094
[X14 = 3,00]	,023	,880	[X14 = 3,00]	,338	,561
[X14 = 4,00]	.	.	[X14 = 4,00]	.	.
[X15 = 1,00]	,000	,994	[X15 = 1,00]	,000	,994
[X15 = 2,00]	2,522	,112	[X15 = 2,00]	,168	,682
[X15 = 3,00]	,280	,596	[X15 = 3,00]	8,722	,003
[X15 = 4,00]	.	.	[X15 = 4,00]	.	.

Note: *) significant at $\alpha = 10\%$

Table 3 shows that there are nine significant predictor variables in the category of learning outcomes, this can be seen from the *p-value* $< \alpha = 10\%$. Significant predictor variable are X2, X4, X8, X10, X11, X12, X13, X14, X15.

Model Fit Test

After doing simultaneous tests and individual testing to determine whether the model developed is appropriate or not, to determine whether there is a discrepancy between the observed results and the expected results, the model appropriateness test is conducted.

Table 4. Model Fit Test of Multinomial Logistic Regression

	Chi-Square	Sig
Deviance	260,984	0,998

The test statistic used to test the fit of the model is the Deviance statistic. With the hypothesis being tested are:

H_0: multinomial logistic regression model is fit (there is no difference between the observed results and the possible prediction results of the model)
H_1: multinomial logistic regression model is not fit (there is a difference between the observed results and the possible prediction results of the model)

The model appropriateness test results are shown in Table 4 thanks to the SPSS program.

Based on the output of the SPSS software in Table 4, the p-value in the Deviance test statistic is 0,998 $> \alpha = 0, 10$ so that H_0 is fit and it can be concluded that multinomial logistic regression is fit.

Interpretation of the Multinomial Logistic Regression Model

An individual test has been conducted to identify the predictor variables that significantly affect student learning results, as stated at point 4.3.2. Additionally, in order to determine the likelihood that students would demonstrate learning outcomes in the area of midterm exam results, it is necessary to interpret the logit function and the odds ratio values shown in Table 5.

The analysis was carried out on parameter estimates using multinomial logistic regression. It is known that there are two logit models formed, namely category 1 (low midterm score category) and category 2 (medium midterm score category), where the last category (high midterm score category) is used as a reference for each categorical predictor variable that is the first logit of variable X_2 with category 3, X_{10} with category 3, X_{11} with category 2, and X_{12} with category 2, at the significance level $\alpha = 10\%$, meanwhile the second logit of variable X_4 with category 2, X_4 with category 3, X_8 with category 3, X_{10} with category 3, X_{11} with category 3, X_{13} with category 3, X_{14} with category 2, and X_{15} with category 3, at the significance level $\alpha = 10\%$.

The multinomial logistic regression model that was produced as a result of the data processing is as follows:

a. Multinomial Logistic Regression Model for first Logit (Low):

$$\mathrm{Logit}_1 = -16, 951 - 2, 050X_2(3) + 2, 619X_{10}(3) - 2, 263X_{11}(2) + 4, 071X_{12}(2)$$

b. Multinomial Logistic Regression Model for second Logit (Medium):

$$\begin{aligned}\mathrm{Logit}_2 = &- 0, 538 + 3, 312X_4(2) + 2, 912X_4(3) - 1, 1340X_8(3) + 1, 529X_{10}(3)\\ &+ 1, 576X_{11}(3) + 1, 622X_{13}(3) + 1, 481X_{14}(2) - 2, 666X_{15}(3)\end{aligned}$$

Table 5. Estimation of Parameters and Odds ratios of Multinomial Logistic Regression Models

Predictor	**B**	**Odd Rasio**	**Predictor**	**B**	**Odd Rasio**
Logit 1 (Low)			**Logit 2 (Medium)**		
Intercept	-16,951		Intercept	-,538	
[X1 = 2,00]	-2,366	,094	[X1 = 2,00]	-1,666	,189
[X1 = 3,00]	-,546	,579	[X1 = 3,00]	-,333	,717
[X1 = 4,00]	0^b	.	[X1 = 4,00]	0^b	.
[X2 = 1,00]	-3,809	,022	[X2 = 1,00]	2,380	10,809
[X2 = 2,00]	-16,892	4,612E-008	[X2 = 2,00]	7,401	1638,321
[X2 = 3,00]	-2,050	,129	[X2 = 3,00]	-,343	,710
[X2 = 4,00]	0^b	.	[X2 = 4,00]	0^b	.
[X3 = 1,00]	32,630	148249075413521,840	[X3 = 1,00]	29,948	10145735299034,475
[X3 = 2,00]	-,349	,706	[X3 = 2,00]	-1,669	,188
[X3 = 3,00]	-1,244	,288	[X3 = 3,00]	-1,575	,207
[X3 = 4,00]	0^b	.	[X3 = 4,00]	0^b	.
[X4 = 1,00]	-15,599	1,680E-007	[X4 = 1,00]	-20,339	1,468E-009
[X4 = 2,00]	1,272	3,567	[X4 = 2,00]	3,312	27,453
[X4 = 3,00]	,813	2,255	[X4 = 3,00]	2,912	18,389
[X4 = 4,00]	0^b	.	[X4 = 4,00]	0^b	.
[X5 = 2,00]	,681	1,975	[X5 = 2,00]	-,121	,886
[X5 = 3,00]	-,157	,854	[X5 = 3,00]	-,650	,522

(*continued*)

Table 5. (*continued*)

Predictor	B	Odd Rasio	Predictor	B	Odd Rasio
Logit 1 (Low)			**Logit 2 (Medium)**		
[X5 = 4,00]	0[b]	.	[X5 = 4,00]	0[b]	.
[X6 = 2,00]	16,649	17005469,063	[X6 = 2,00]	8,324	4119,565
[X6 = 3,00]	,499	1,647	[X6 = 3,00]	,250	1,284
[X6 = 4,00]	0[b]	.	[X6 = 4,00]	0[b]	.
[X7 = 2,00]	-2,399	,091	[X7 = 2,00]	-,790	,454
[X7 = 3,00]	,065	1,068	[X7 = 3,00]	,419	1,520
[X7 = 4,00]	0[b]	.	[X7 = 4,00]	0[b]	.
[X8 = 1,00]	22,184	4310927755,230	[X8 = 1,00]	-,466	,628
[X8 = 2,00]	-,924	,397	[X8 = 2,00]	-,940	,391
[X8 = 3,00]	-,890	,411	[X8 = 3,00]	-1,340	,262
[X8 = 4,00]	0[b]	.	[X8 = 4,00]	0[b]	.
[X9 = 1,00]	-2,704	,067	[X9 = 1,00]	-18,669	7,799E-009
[X9 = 2,00]	15,134	3736049,939	[X9 = 2,00]	-,320	,726
[X9 = 3,00]	16,104	9864497,914	[X9 = 3,00]	-,353	,702
[X9 = 4,00]	0[b]	.	[X9 = 4,00]	0[b]	.
[X10 = 1,00]	2,469	11,807	[X10 = 1,00]	1,832	6,248
[X10 = 2,00]	1,462	4,315	[X10 = 2,00]	,882	2,417

(*continued*)

Table 5. (*continued*)

Predictor	B	Odd Rasio	Predictor	B	Odd Rasio
Logit 1 (Low)			**Logit 2 (Medium)**		
[X10 = 3,00]	2,619	13,716	[X10 = 3,00]	1,529	4,614
[X10 = 4,00]	0[b]	.	[X10 = 4,00]	0[b]	.
[X11 = 1,00]	14,786	2639724,889	[X11 = 1,00]	7,337	1535,950
[X11 = 2,00]	-2,263	,104	[X11 = 2,00]	-,595	,551
[X11 = 3,00]	-,066	,936	[X11 = 3,00]	1,576	4,836
[X11 = 4,00]	0[b]	.	[X11 = 4,00]	0[b]	.
[X12 = 2,00]	4,071	58,608	[X12 = 2,00]	2,303	10,003
[X12 = 3,00]	1,013	2,753	[X12 = 3,00]	,755	2,128
[X12 = 4,00]	0[b]	.	[X12 = 4,00]	0[b]	.
[X13 = 1,00]	-16,484	6,932E-008	[X13 = 1,00]	10,656	42427,068
[X13 = 2,00]	-,779	,459	[X13 = 2,00]	,022	1,023
[X13 = 3,00]	-,016	,984	[X13 = 3,00]	1,622	5,064
[X13 = 4,00]	0[b]	.	[X13 = 4,00]	0[b]	.
[X14 = 1,00]	32,141	90919179363892,030	[X14 = 1,00]	31,413	43895868972176,770
[X14 = 2,00]	1,157	3,179	[X14 = 2,00]	1,481	4,399
[X14 = 3,00]	,172	1,188	[X14 = 3,00]	,507	1,660
[X14 = 4,00]	0[b]	.	[X14 = 4,00]	0[b]	

(*continued*)

Table 5. (*continued*)

Predictor	B	Odd Rasio	Predictor	B	Odd Rasio
Logit 1 (Low)			**Logit 2 (Medium)**		
[X15 = 1,00]	15,548	5652615,744	[X15 = 1,00]	14,436	
[X15 = 2,00]	2,369	10,691	[X15 = 2,00]	-,475	
[X15 = 3,00]	-,640	,527	[X15 = 3,00]	-2,666	
[X15 = 4,00]	0^b	.	[X15 = 4,00]	0^b	

The multinomial logistic regression model's likelihood of formation is:

1. The probability of a multinomial logistic regression model for the high midterm score category:

$$\pi_0 x_i = \frac{1}{1 + \exp\left(Logit_1\right) + \exp\left(Logit_2\right)}$$

2. The probability of a multinomial logistic regression model for the low midterm score category:

$$\pi_1 x_i = \frac{exp\left(Logit_1\right)}{1 + \exp\left(Logit_1\right) + \exp\left(Logit_2\right)}$$

3. The probability of a multinomial logistic regression model for the medium midterm score category:

$$\pi_2 x_i = \frac{exp\left(Logit_2\right)}{1 + \exp\left(Logit_1\right) + \exp\left(Logit_2\right)}$$

After the model is obtained, the next step is to carry out interpretation to obtain conclusions from parameter estimation. Interpretation of multinomial logistic regression uses odds ratios to determine the relationship tendency of a predictor variable to a response variable. The odds ratio for each logit based on parameter estimates is shown in Table 6.

Table 6 shows the odds ratio with the high midterm score category as a comparison response variable, it is concluded that:

a. Students who have interest and motivation in this regard, namely having the desire to achieve good results in learning to make orangutans proud have a tendency of 0.129 times to have learning outcomes (low midterm scores) compared to learning

Table 6. *Odds Ratio* of The First Logit (Category of Low Midterm Score)

Logit	Predictor variable	Category	β_{jk}	$exp(\beta_{jk})$
The first Logit (Category of low midterm score)	X_2 (Interest and Motivation)	3	-2,050	0,129
	X_{10} (Learning Method)	3	2,619	13,716
	X_{11} (Learning Method)	2	-2,263	0,104
	X_{12} (Learning Method)	2	4,071	58,608

outcomes (high midterm scores), so that the lower the interest and motivation, student learning outcomes (midterm scores) tend to be low.

b. Students who have a way of learning in this case 'often' ask the lecturer if there is learning material that is not understood has a tendency of 13,716 times will have learning outcomes (low midterm scores) compared to learning outcomes (high midterm scores), so that the lower the way students learn, student learning outcomes (midterm scores) tend to be low.
c. Students who have a way of learning, in this case 'sometimes' read other references to support learning activities, have a tendency of 0.104 times to have learning outcomes (low midterm scores) compared to learning outcomes (high midterm scores), so that the lower the student learning method, the higher the learning outcomes. Learning (midterm scores) students tend to be low.
d. Students who have a way of learning in this case 'sometimes' are able to account for the results of answers to assignments that have been done, have a tendency of 58,608 times will have learning outcomes (low midterm Score) compared to learning outcomes (high midterm score), so the lower the learning method students, student learning outcomes (midterm scores) tend to be low.

For interpretation with Logit 2, it is the same as Logit 1.

5 Conclusion

The study of the data revealed the following conclusions:

a. Based on the output of the SPSS software in Table 2 obtained *p-value* 0,000 $< \alpha =$ 0.10 then H_0 is rejected. This can be interpreted that there is at least one predictor variable that influences the category of learning outcomes.
b. According to Table 3, there are nine significant predictor factors in the category of learning outcomes, as indicated by the p-value of 10%.The significant predictor variables are X_2, X_4, X_8, X_{10}, X_{11}, X_{12}, X_{13}, X_{14}, X_{15}.
c. The multinomial logistic regression model is determined to be fit based on the output of the SPSS software in Table 4, where the p-value for the Deviance test statistic is 0,998 $>=$ 0,10 and H0 is accepted.
d. Students who have interest and motivation in this regard, namely having the desire to achieve good results in learning to make orangutans proud have a tendency of

0.129 times to have learning outcomes (low midterm scores) compared to learning outcomes (high midterm scores), so that the lower the interest and motivation, student learning outcomes (midterm scores) tend to be low.

e. Students who have a way of learning in this case 'often' ask the lecturer if there is learning material that is not understood has a tendency of 13,716 times will have learning outcomes (low midterm scores) compared to learning outcomes (high midterm scores), so that the lower the way students learn, student learning outcomes (midterm scores) tend to be low.
f. Students who have a way of learning, in this case 'sometimes' read other references to support learning activities, have a tendency of 0.104 times to have learning outcomes (low midterm scores) compared to learning outcomes (high midterm scores), so that the lower the student learning method, the higher the learning outcomes. Learning (midterm scores) students tend to be low.
g. Students who have a way of learning in this case 'sometimes' are able to account for the results of answers to assignments that have been done, have a tendency of 58,608 times will have learning outcomes (low midterm score) compared to learning outcomes (high midterm score), so the lower the learning method students, student learning outcomes (midterm scores) tend to be low.

For interpretation with Logit 2, the steps are the same as for Logit 1.

References

1. M. Douglas, S. V. Katikireddi, M. Taulbut, M. McKee, and G. McCartney, "Mitigating the wider health effects of covid-19 pandemic response," *BMJ*, vol. 369, no. April, pp. 1–6, 2020, doi: https://doi.org/10.1136/bmj.m1557.
2. H. Legido-Quigley, J. T. Mateos-García, V. R. Campos, M. Gea-Sánchez, C. Muntaner, and M. McKee, "The resilience of the Spanish health system against the COVID-19 pandemic," *Lancet Public Heal.*, vol. 5, no. 5, pp. e251–e252, 2020, doi: https://doi.org/10.1016/S2468-2667(20)30060-8.
3. J. Cordeiro, "Emergency Remote Teaching and Learning," pp. 140–159, 2022, doi: https://doi.org/10.4018/978-1-7998-9538-1.ch008.
4. M. Samir Abou El-Seoud, I. A. T. F. Taj-Eddin, N. Seddiek, M. M. El-Khouly, and A. Nosseir, "E-learning and students' motivation: A research study on the effect of e-learning on higher education," *Int. J. Emerg. Technol. Learn.*, vol. 9, no. 4, pp. 20–26, 2014, doi: https://doi.org/10.3991/ijet.v9i4.3465.
5. V. A. Nguyen, "The Impact of Online Learning Activities on Student Learning Outcome in Blended Learning Course," *J. Inf. Knowl. Manag.*, vol. 16, no. 4, 2017, doi: https://doi.org/10.1142/S021964921750040X.
6. L. Salamat, G. Ahmad, M. I. Bakht, and I. L. Saifi, "EFFECTS OF E – LEARNING ON STUDENTS ' ACADEMIC LEARNING AT EFFECTS OF E – LEARNING ON STUDENTS ' ACADEMIC LEARNING AT UNIVERSITY LEVEL Lubna Salamat Mohammad Iftikhar Bakht Imran Latif Saifi," *Assian Innov. J. Soc. Sci. Humanit.*, vol. 2 (2), no. July, pp. 1–12, 2018, doi: https://doi.org/10.13140/RG.2.2.18234.49609.
7. B. Raj Acharya, "Factors Affecting Difficulties in Learning Mathematics by Mathematics Learners," *Int. J. Elem. Educ.*, vol. 6, no. 2, p. 8, 2017, doi: https://doi.org/10.11648/j.ijeedu.20170602.11.

8. Y. Li and A. H. Schoenfeld, "Problematizing teaching and learning mathematics as 'given' in STEM education," *Int. J. STEM Educ.*, vol. 6, no. 1, 2019, doi: https://doi.org/10.1186/s40594-019-0197-9.
9. L. F. M. G. Pedro, C. M. M. de O. Barbosa, and C. M. das N. Santos, "A critical review of mobile learning integration in formal educational contexts," *Int. J. Educ. Technol. High. Educ.*, vol. 15, no. 1, 2018, doi: https://doi.org/10.1186/s41239-018-0091-4.
10. L. K. Fryer, K. Nakao, and A. Thompson, "Chatbot learning partners: Connecting learning experiences, interest and competence," *Comput. Human Behav.*, vol. 93, no. December 2018, pp. 279–289, 2019, doi: https://doi.org/10.1016/j.chb.2018.12.023.
11. A. Azmidar, D. Darhim, and J. A. Dahlan, "Enhancing Students' Interest through Mathematics Learning," *J. Phys. Conf. Ser.*, vol. 895, no. 1, 2017, doi: https://doi.org/10.1088/1742-6596/895/1/012072.
12. K. A. Renninger and S. E. Hidi, "Interest development and learning.," *The Cambridge handbook of motivation and learning.* Cambridge University Press, New York, NY, US, pp. 265–290, 2019. doi: https://doi.org/10.1017/9781316823279.013.
13. A. Omidiandost, Y. Sohrabi, M. Poursadeghiyan, H. Yarmohammadi, and A. Mosavi, "Evaluation of General and Local Lighting as an Environmental Ergonomics Factor in Different parts of a Hospital in the City of Kermanshah in 2015," *Tech. J. Eng. Appl. Sci. ©2015 TJEAS J.*, vol. 5, no. 3, pp. 255–259, 2015, [Online]. Available: www.tjeas.com
14. *et al.*, "Evaluación Ergonómica En El Módulo De Préstamos De Una Biblioteca De Universidad Pública," *Rev. Ing. Ind.*, vol. 17, no. 2, pp. 171–186, 2018, doi: https://doi.org/10.22320/s07179103/2018.10.
15. P. J. Lee, B. K. Lee, J. Y. Jeon, M. Zhang, and J. Kang, "Impact of noise on self-rated job satisfaction and health in open-plan offices: a structural equation modelling approach," *Ergonomics*, vol. 59, no. 2, pp. 222–234, 2016, doi: https://doi.org/10.1080/00140139.2015.1066877.
16. F. P. da Silva, "Mental Workload, Task Demand and Driving Performance: What Relation?," *Procedia - Soc. Behav. Sci.*, vol. 162, no. Panam, pp. 310–319, 2014, doi: https://doi.org/10.1016/j.sbspro.2014.12.212.
17. R. G. Montero, "Artículo Original," *Rev. Peru. Epidemiol. RPEonline*, vol. 15, no. 1, pp. 1–5, 2011.
18. พวงผกา มะเสนา และประณต นันทิยะกุล, "Applied Logistic Regression," *วารสารวิชาการมหาวิทยาลัยอีสเทิร์นเอเชีย*, vol. 4, no. 1, pp. 88–100, 2557.
19. A. M. El-Habil, "An application on multinomial logistic regression model," *Pakistan J. Stat. Oper. Res.*, vol. 8, no. 2, pp. 271–291, 2012, doi: https://doi.org/10.18187/pjsor.v8i2.234.