Non-Academic Factors Analysis Impacting Students' Online Learning During the COVID-19 Pandemic in Universitas Logistic and Bisnis Internasional

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***Abstract*—In education, online learning with an e-learning system is an irreplaceable need. Many argue that online learning is the current educational crisis. Several studies show how complicated the handling of COVID-19 for universities is, especially in online learning (e-learning) outcomes. The variables influencing online learning during the COVID-19 epidemic have been shown in numerous studies. However, the influence of several other factors still needs to be investigated. Therefore, this study aims to determine non-academic factors that affect online learning during the COVID-19 pandemic. With data collected from the International University of Logistics and Business (ULBI), this study uses Cronbach's-Alpha analysis, Bayesian Exploratory Factor Analysis (BEFA), Principal Component Analysis (PCA), and Multivariate Regression Analysis. The evaluation of the research scale shows 20 observed variables. The test results prove that three non-academic factors influence students' online learning outcomes during the COVID-19 pandemic: education cost policy (H1), communication quality (H2), and student support (H3). Each factor has $p-value < 0.001$, $p-value = 0.029$, and $p-value = 0.004$, respectively. Meanwhile, family circumstances do not affect students' online learning outcomes during the COVID-19 pandemic (H4 rejected) because the p-value is 0.152. An example case in the questionnaire shows that most students say family income can adapt to changes during the COVID-19 pandemic.**

***Index Terms*—cronbach's alpha, BEFA, PCA, multivariate regression analysis, COVID-19, online learning, academic**

I. Introduction

Coronavirus disease 2019 (COVID-19) was detected in China at the end of 2019, spreading very quickly throughout Indonesia in just a few months [1]. Moreover, WHO officially declared a pandemic on March 11, 2020, [2]. In addition, the Government of Indonesia simultaneously confirms that COVID-19 is a serious public health [3]. In education, online learning with an e-learning system is an irreplaceable need. Many argue that online learning is the current educational crisis [4]. Several studies show how complicated the handling of COVID-19 for universities is, especially in online learning outcomes (e-learning) [5].

In previous studies, apart from academic factors, some students were constrained and unable to carry out online learning due to several non-academic factors [6]. These non-academic factors include the campus education fee policy when e-learning, online learning does not feel the same because the discussion does not run as naturally as face-to-face, colleague support to students during e-learning, campus scholarship policies, and services received during e-learning [7]. However, some limitations exist in previous research.

Previous studies have also been carried out and found that the work status of parents affects the resilience of carrying out online learning [8]. It required the willingness and effort of students to study independently, with the value of independent learning and satisfaction with online classes [9].

This study intends to create a novel technology acceptance model (TAM) that explains non-academic factors that affect online learning results of the COVID-19 pandemic education by developing the limitations of previous research. We gather data from the International University of Logistics and Business (ULBI), Indonesia. This study uses Cronbach's Alpha analysis, BEFA, PCA, and multivariate regression analysis with the OLS. The research observes 20 variables.

There are two contributions to research in this paper:

- A proposal of four new hypotheses regarding non-academic factor analysis impacting students' online learning during the COVID-19 pandemics
- A new case study on online learning, namely ULBI

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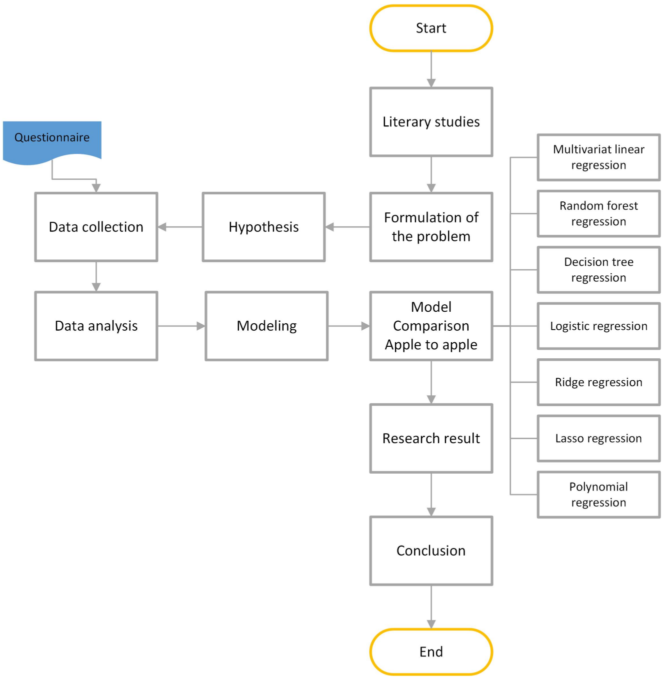

Fig. 1. The research methodology flowchart.

II. Research Method

Figure 1 explains the flowchart of the research methodology, which consists of 9 stages: literature review, problem formulation, hypothesis, data collection, data analysis, modeling, apple to apple comparison model, results, and conclusions.

A. Research Preparation

The education cost policy discusses the extent to which the campus (education staff, management) believes that online learning policies related to education costs can help relieve students during the COVID-19 pandemic when developing learning outcomes. Online learning is to help learners keep travel time and costs [10]. In addition, students have been assessed through behavioral transformation, fear, and show signs of a panic situation, hopelessness, lack of communication, afraid, worry, flurry, and passiveness during periods of insulation [11]. Therefore, it is important to emphasize that distance learning is appropriate for students to gather to understand student characteristics and identify potential learning barriers, student support, tuition fees, learning feedback, communication with teachers, student services, and family circumstances. We obtained the following hypothesis design in this study based on learning outcomes during the COVID-19 pandemic:

- H1: education cost policy factors affect student technology
- H2: communication quality factors affect student technology
- H3: student support factors affect student technology
- H4: family circumstances factors affect student technology

The widely used model to confirm acceptance of a particular technology is the TAM. Fred D. Davis Initiated TAM in 1986 to assess the propensity of users to accept or use new

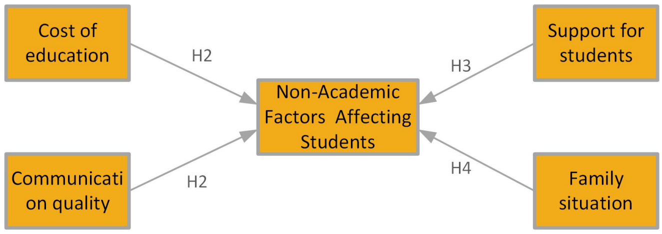

Fig. 2. Proposed model.

systems and technologies. Its original creation was to predict user behavior towards using computers and information technology. This model also Interprets the adoption of new types of technology by agencies and communities (Davis et al., 1989) [12]. Fig. 2 is a theoretical framework that shows the research hypothesis.

This study utilizes quantitative methods in data collection with a total of 611 respondents who are active students of the University of Logistics and International Business, with a target percentage of 30% for each study program, with a total of 10 study programs. The questionnaire method by asking questions is via WhatsApp. The data collected is local data from Pos Indonesia Polytechnic students based on study programs from April 2022 to August 2022.

A five-point Likert scale is for all variables studied from each factor. A 5-point Likert scale was used, 1 = strongly disagree, 2 = disagree, 3 = norm, 4 = agree, and 5 = strongly agree. Data size is for the estimated number of parameters, and if we use the maximum likelihood method (ML), the minimum data size is 100 until 150. Apart from that, the required ratio for the data sample design is at least five observations per each parameter estimate for the ratio (5:1) [13]. This study has 20 parameter estimates. Therefore a minimum sample size of 140 observations is required. Practical research explains that the required sample size is 150 or greater than 150 to obtain parameter estimates with a fairly small standard error [14].

We parse the equations to produce a sample with a large population [15]. Because the student community at the University of Logistics and International Business is very large, the authors use the following equation:

$$n = \frac{Z^2 p(1-p)}{e^2} \tag{1}$$

where n denotes the sample size, Z is the normal abscissa curve reducing the area in the tail (1- balanced with required 95% confidence level), e denotes the level of accuracy required, p denotes an estimate of the proportion of attributes that exist in the population. Next, we choose a confidence level of 95%, so for the value of $Z = 1.96$. We set the approximate proportion to 0.5. The required level accuracy is taken as) $e = 5\%$. The lowest sample rate in this study is 384 data samples.

We surveyed all students of each study program at ULBI through a questionnaire sent via the WhatsApp application. The duration of the survey is from April 2022 to August 2022. With the explanation of the following factors:

- The observed variables, X1, X2, X3, and X4, represent the education cost policy. This factor is X.

TABLE I
PERCENTAGE OF EACH STUDY PROGRAM FROM THE TOTAL NUMBER OF STUDENTS

Study Program	***Sample***	***Respondents***	*%*
Diploma of Informatics Engineering	69	31	44,92
Bachelor of Applied Informatics Engineering	261	80	30,65
Diploma of Informatics Management	59	23	38,98
Diploma of Accounting	76	23	30,26
Bachelor of Applied Financial Accounting	190	58	30,52
Diploma of Marketing Management	73	23	31,50
Bachelor of Applied Company Management	304	92	30,26
Diploma of Logistics Administration	265	93	35,09
Bachelor of Applied Business Logistics	586	176	30,03
Bachelor of Applied E-Commerce	38	12	31,57
Total	1921	611	

- The observed variables, I1, I2, I3, and I4, represent the quality of communication. This factor is I.
- The observed variables, J1, J2, J3, and J4, represent student support. This factor is J.
- The observed variables, K1, K2, K3, and K4, represents family circumstances. This factor is K.

We hypothesize that four non-academic factors affect students' online learning outcomes during the COVID-19 pandemic in strong to weak order: education cost policies, student support, communication quality, and family circumstances.

Table I explains that as many as 611 respondents fulfill the minimum percentage of 30% of each study program. With a response rate of 100%. After that, we used 611 respondents from the questionnaire for this research.

B. Cronbach's Alpha Analysis and BEFA

We performed a step to check the scale's reliability using Cronbach's Alpha coefficients, BEFA, and multivariate regression analysis using the OLS. According to [16], this includes observed variables with corrected item-$total\ correlation \geq$ 0.3 and $Cronbach's\ Alpha \geq$ 0.6 to ensure scale reliability. Furthermore, at this stage, the analysis and ranking of the discussion of the problem results are carried out by checking the correlation matrix and reliability tests. BEFA produces a posterior distribution of all parameters. As a result, the posterior distribution includes the possibility, which provides information about the version statistics. The entire basis of the parameters is on the data under study, compared to the preceding distribution, which essentially incorporates statistics settings from the previous version's study data. First, Bayes' rule brings together the distribution and possibility defining characteristics for a posterior distribution:

$$posterior \propto likelihood \times prior \tag{2}$$

We use simulation to estimate post-distribution. The Markov Chain Monte Carlo (MCMC) can simulate a complex capable posterior model through varying accuracy. However, defining an efficient sample collecting strategy and confirming that MCMC converges to the posterior distribution is frequently challenging. In addition, we must determine the prior distribution for all model parameters in the BEFA model, while the prior distribution or priority considered a key component, so the selection must be careful. The equation for the factor analysis model:

$$\begin{aligned} X_i &= \lambda \times F_i + u_i, \\ F_i &\sim N(0, R), \\ u_i &\sim N(0, \Sigma), \\ \Sigma &= diag(\sigma_1^2, \sigma_2^2, \ldots, \sigma_m^2), \end{aligned} \tag{3}$$

$X_i = (X_{i1}), \ldots, X_{im})^l$ denotes a vector that includes the variable m for the individual $i = 1, 2, \ldots, N$. The residual idiosyncratic term is denoted by $u_i = (u_{i1}, \ldots, u_{im})^l$. The latent common factor of the model is identified by $F_i = (F_{i1}, F_{i2}, \ldots, F_{ik})^l$. Then λ is an assignment that shows the relationship between the observed variable X and the common latent factor F.

In order to assign the variables under consideration to each factor, we employed a binary index matrix, which is a benchmark for a factor loading matrix λ [17]. The latent variable gets information by each row of which component matches the load. For instance, when the variable m joins the factor k, the line m becomes the indicator vector ek:$\lambda\Delta m$:

$$\triangle_m = (0, \ldots, 0, \underbrace{1}_{kth\ element}, 0, \ldots, 0) \equiv e_k \tag{4}$$

When a variable contains no factors, the matching row contains only zeros. We believe that no variable can store more than one factor. That signifies $\Sigma_k \Delta_{mk} \leq 1$. BEFA test, determine priority distribution for $\tau_k \tau_k = Pr(\Delta_m = e_k | \tau_k)$, the probability that the variable is loaded on the k factor (idiosyncratic variance), (factor assignment), and (factor correlation matrix). In this research, we used an earlier distribution for this parameter, as if recommended in [17] i.e. σ_m^2, λ, R. The sum of the latent K factors is defined by the Ledermann [18] bounds. However, during the collection of the MCMC sample, random exploration of the factor loading matrix may create a 0 column, thus cutting off the latent variable. The amount of MCMC iteration is 27500. MCMC sampler burn-in period 2500. Therefore, the saved MCMC iteration amount for posterior inference (after burn-in) is 25000.

PCA is needed to observe variables that represent online learning outcomes. The observed variable only measures one factor: student online learning outcomes. Before carrying out the PCA process, the researcher first looked at Cronbach's Alpha variable. Next, do the PCA process. The initial stage must meet several conditions before we carry out the PCA process. Kaiser-Mayer-Olkin (KMO) is an examination to check data consistency for factor analysis [19]. The level of acceptance of KMOs with values from 0.7 to 1.0 is good and superb, while KMOs from 0 to 0.6 are unacceptable and mediocre.

TABLE II
SCALE RELIABILITY TEST RESULTS

Scale	*Alpha*	*Std.Alpha*	*r(item, total)*	*Cronbach's Alpha*
X1	0.9819	0.9819	0.8354	0.9827
X2	0.9818	0.9818	0.8468	
X3	0.9826	0.9826	0.7512	
X4	0.9816	0.9816	0.8763	
I1	0.9816	0.9816	0.8735	0.9827
I2	0.9814	0.9814	0.8895	
I3	0.9826	0.9826	0.8414	
I4	0.9818	0.9818	0.8489	
J1	0.9814	0.9814	0.8932	0.9827
J2	0.9815	0.9815	0.8834	
J3	0.9814	0.9814	0.8939	
J4	0.9814	0.9814	0.8930	
K1	0.9817	0.9817	0.8735	0.8602
K2	0.9816	0.9816	0.8756	
K3	0.9815	0.9815	0.8845	
K4	0.9815	0.9815	0.8817	
G1	0.9822	0.9822	0.7990	0.9827
G2	0.9823	0.9823	0.7933	
G3	0.9822	0.9822	0.7988	
G4	0.9820	0.9820	0.8228	

C. Multivariate regression analysis

Multivariate regression analysis using the OLS method evaluates non-academic factors that affect students' online learning results and tests hypotheses. The specific models are as follows:

$$SP_i = \beta_0 + \beta \times F_i + \varepsilon_i, \tag{5}$$

which shows students' online learning outcomes, for individual $i = 1, 2, \ldots, N$. Residual idiosyncratic denoted $SP_i F_i = (F_{i1}, F_{i2}, \ldots, F_{ik})^l$. The latent common factor of the model is denoted $F_i = (F_{i1}, F_{i2}, \ldots, F_{ik})^l$ shows the factors of the BEFA results. Here, the calculation takes the average of the variables studied, indicating that the error term shows the coefficient matrix in the model. Next, β is the matrix coefficient. Lastly, ε_i is the error value.

The regression model is a machine learning method with the category of supervised learning with the target data in the form of numerical data. Regression is a method for modeling the relationship between the dependent variable or the target y through one or more independent variables x. Regression is for prediction and modeling based on existing data. Simple linear regression is regression modeling based on one predictor variable.

III. RESULTS AND DISCUSSION

A. Results

In the confidence test using Cronbach's Alpha, where $Cronbach's\ Alpha \geq 0.60$ means reliable, $Cronbach's\ Alpha \leq 0.60$ means not reliable [20]. Table II explains that $Cronbach's\ Alpha$ value for all items is 0.9827, which is reliable because it is larger than the threshold. The $Cronbach's\ Alpha$ value for each variable ranges from 0.9814 to 0.9826, all of which are larger than the reliability threshold. The determination results show that all the scales and the observed variables, a total of 20, all reach the reliability value. Therefore the research can proceed to the exploratory factor analysis stage.

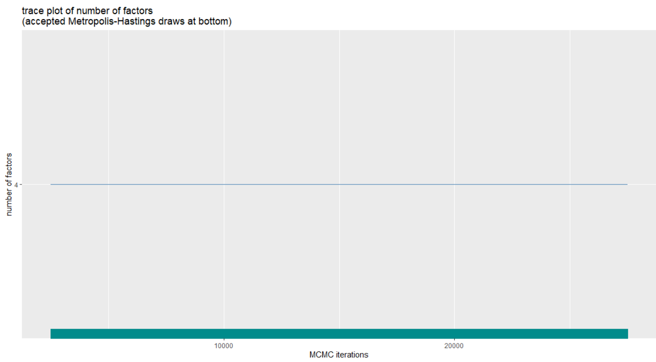

Fig. 3. Scale reliability test results.

TABLE III
POSTERIOR MEAN OF FACTOR LOADING COEFFICIENT

alpha	*dedic*	*prob*	*mean*	*sd*	*95% hpd*	
X1	1	1	0.867	0.032	0.804	0.931
X2	1	1	0.929	0.031	0.865	0.987
X3	1	1	0.807	0.034	0.740	0.874
X4	2	1	0.895	0.031	0.835	0.957
I1	3	1	0.903	0.031	0.845	0.967
I2	2	1	0.922	0.031	0.861	0.981
I3	3	1	0.863	0.032	0.801	0.927
I4	2	1	0.873	0.032	0.810	0.935
J1	3	1	0.918	0.031	0.858	0.977
J2	3	1	0.921	0.031	0.862	0.983
J3	3	1	0.927	0.031	0.869	0.988
J4	3	1	0.914	0.031	0.853	0.973
K1	4	1	0.889	0.032	0.829	0.952
K2	4	1	0.930	0.031	0.872	0.991
K3	4	1	0.929	0.031	0.870	0.989
K4	4	1	0.925	0.031	0.868	0.988

In this stage, the BEFA method identifies the relationship between variables and observes variables representing education cost policies, quality of communication, student support, and family circumstances. Fig. 3 explains that the MCMC size used is 25000 and tells that the posterior mean of the number of factors is 4. In addition, the posterior distribution also shows that the probability value (probability) of BEFA being able to extract the four factors is 100%.

Tab. III describes the observed variable allocation for each component. The test findings reveal that each observed variable's average posterior factor coefficient, which is more than 0.5, ranges in value from 0.807 to 0.930.

Fig. 4 describes the visualization of the observed variables for each factor. Therefore, BEFA has extracted four factors and variables observed in each factor with a factor loading coefficient value greater than 0.5. Each cell has a value above 0.5, meaning that each manifest variable can be represented by its latent factor.

First, the KMO value is small, 0.5, while the significance of Bartlett's test should be less than 0.05. Bartlett' test must have $p-value \leq 0.001$. The overall KMO value is 0.88, while the MSA value of one variable representing online learning outcomes G1, G2, G3, and G4 is 0.88, 0.88, 0.87, and 0.88, respectively. Table IV shows the result. As for the value of Bartlett' test p-value $\leq$ 2.2e-16, which means Bartlett' test p-value $\leq$ 0.05.

In the PCA test with four principal components, there is one main factor with eigenvalues above 1. The principal component has the value of 3.5893692, which means there is one formed factor. Fig. 5 shows the eigenvalue curve for each principal component. Because the two met conditions, this research can continue to the stage of the Factor Analysis process.

Table V shows the results of the OLS analysis. Unstandardized coefficient beta shows the slope of the OLS analysis. The greater the slope, the better the variable. From the analysis results, the largest slope is variable X, while the lowest slope is variable K. The unstandardized coefficient standard error shows the distribution of the data. The smaller the value, the smaller the distribution. The variable with the smallest standard error is K, while the largest is I. The standardized coefficient beta shows the correlation—the greater the value, the better the correlation with the dependent variable. X has the largest standardized coefficient beta value, then K has the smallest value. Finally, the p-value shows significance. Values below 0.05 indicate that the variable has significance. X, I, and J have significance, while K has no significance.

Finally, Table VI shows the effect of each variable through its unstandardized variable coefficient beta value. In addition, the table also shows accepted variables' hypotheses and rejected ones. We reject H4 because it has an insignificant p-value. An example case in the questionnaire shows that most students say that family income can adapt to changes during the COVID-19 pandemic.

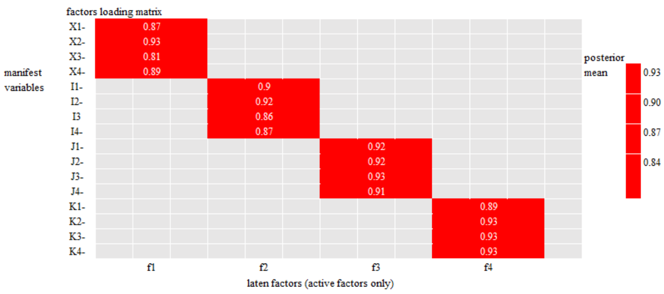

Fig. 4. Factor loading matrix.

TABLE IV
POSTERIOR MEAN OF FACTOR LOADING COEFFICIENT

KMO factor adequacy Call: 0.88			
Bartlett' test p-value $\leq$ 2.2e-16			
MSA for each item			
G1	**G2**	**G3**	**G4**
0.88	0.88	0.87	0.88

TABLE V
OLS RESULT

Variable	Unstandardized Coef.		Standardized Coef. Beta	t	P-Value
	Beta	Std. Error			
Constant	0.079	0.017		4.693	0.000
X	0.391	0.061	0.375	6.367	0.000
I	0.162	0.074	0.165	2.191	0.029
J	0.192	0.067	0.206	2.888	0.004
K	0.085	0.059	0.089	1.433	0.152

TABLE VI
NON-ACADEMIC FACTORS IMPACTING STUDENTS' ONLINE LEARNING DURING THE COVID-19 PANDEMIC IN ULBI

Code	*Explanation*	*Factor*	*Coef.*	*Hypothesis*
X1	Campus education fee policy when e-learning	Cost of education	0.391	H1 accepted
X2	The services received during e-learning are in accordance with the tuition fees paid			
X3	Cutting education costs during e-learning			
X4	Scholarship policy, for students during e-learning			
I1	Communication with family during e-learning	Communication quality	0.162	H2 accepted
I2	Communication with lecturers during e-learning			
I3	Lack of communication makes you less confident and less enthusiastic about participating in e-learning			
I4	online learning feels the same because the discussion runs as naturally as face-to-face			
J1	Instructor (lecturer) support for students during e-learning and Support for students	Support for students	0.192	H3 accepted
J2	Parental support for students during e-learning			
J3	Support from close friends or college friends to students during e-learning			
J4	Colleague support for students during e-learning			
K1	The number of family dependents during the pandemic makes it comfortable to do e-learning	Family situation	0.085	H4 rejected
K2	With so many family dependents during the pandemic, it makes it comfortable to do e-learning			
K3	The average monthly family income is able to adapt to changes during the COVID-19 pandemic			
K4	Family circumstances, whether financial or economic, affect the implementation of e-learning			

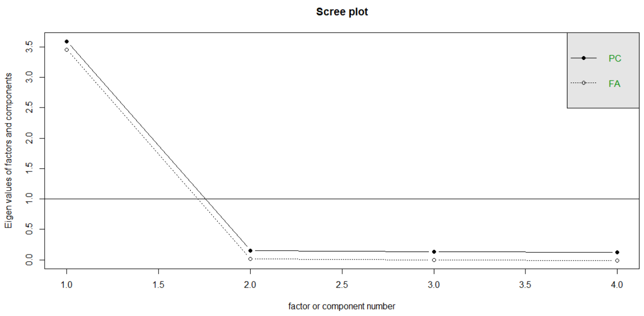

Fig. 5. Eigenvalue of four principal components.

B. Discussion

Other research has implemented TAM on online learning in the middle of the COVID-19 pandemic, such as [21]. The paper suggests five hypothesis, including that acceptance of learning behaviour (A1) is affected by attitude towards learning (A2) and perceived usefulness (PU). Then A1 is also affected by PU and perceived ease of use (PEOU). Lastly, that PU is affected by PEOU. Then our research implements the methodology in the [4] paper, in which the study offers the TAM method with several new metrics related to student online learning outcomes at universities in Ho Chi Min City. Our contribution is twofold. First, we offer four new parameters, of which three have a proven, accepted hypothesis. Then we have a new case study at ULBI.

IV. Conclusion

We used multivariate regression with OLS to create a novel TAM that explains non-academic factors and online learning during the COVID-19 pandemic in ULBI. The test results prove that three non-academic factors influence students' online learning outcomes during the COVID-19 pandemic: education cost policy, communication quality, and student support. Each factor has $p-value < 0.001$, $p-value = 0.029$, and $p-value = 0.004$, respectively. Meanwhile, family circumstances do not affect students' online learning outcomes during the COVID-19 pandemic because the p-value is 0.152. An example case in the questionnaire shows that most students say that family income can adapt to changes during the COVID-19 pandemic.

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