# Determining the online learning challenges during COVID-19 pandemic at the University of Mataram using Principal Component Analysis

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# Determining the Online Learning Challenges during COVID-19 Pandemic at the University of Mataram using Principal Component Analysis

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**Abstract.** The COVID-19 pandemic had an impact on the world of education and it leads to the cancellation of all educational activities. An online learning system was an educational system or concept that utilizes information technology in the teaching and learning process. The basic principles in the online learning process are clarity of messages, learning strategies, interactivity, growth of motivation and creativity, and the use of media for effective communication. The purpose of this study was to determine what factors are hindering students in online lectures by using Principal Component Analysis. The research was conducted using a survey method, namely by filling in forms for undergraduate students at the University of Mataram. The method used to analyze the data was a quantitative descriptive technique which was expressed in the distribution of scores and percentages. This form contains 15 observed variables, after factor analysis was carried out, and obtained 3 factors that most hamper online lectures. The dominant factor is Factor 1 that can explain 28.957% of the variation. The variables included in Factor 1 are the lack of concentration, material understanding, not direct discussion, unconcern (boredom), and lack of study companion variables. The results obtained can be used as a consideration to maximize online lectures during the COVID-19 pandemic.

## INTRODUCTION

At the beginning of 2020, the Coronavirus (COVID)-19 pandemic had an impact on the world of education. In education, the government issued a policy to cancel all educational activities, such as face-to-face teaching and learning [1]. This is intended as a form of effort to prevent the spread of the virus in Indonesia. This policy requires the government to take other alternatives to continue carrying out teaching and learning activities. The alternative used is to carry out teaching and learning activities online. The desired online learning process is message clarity, learning strategies, interactivity, creativity, and the use of media for communication. Along with advances in information and communication technology, today brings various changes in human life [2].

The University of Mataram is one of the universities that have implemented an online learning system, where the media used in this learning is the internet network. The online learning system has been carried out by utilizing the online learning system platform. This web-based learning can be more interactive, because it has no access restrictions and can be accessed anywhere, thus allowing lectures to be conducted without knowing the limitations of time and place. However, online lectures are not as easy as imagined due to circumstances and conditions in various places that do not support the smooth running of online learning. This causes the occurrence of obstacles faced by some students [3].

There are obstacles in online lectures that are challenging for both teachers and students. More awareness is needed relating to the aspects of convenience and accessibility to improve online learning [1]. Based on the described problems, the authors aim to study the obstacles in online learning. These factors will be grouped based on

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the similarity of their characteristics so that they can be identified faster [4]. Based on the results of research that has been done by the author, there are many factors that become challenges in online learning, thus confusing the author's conclusions. Therefore, these factors need to be based on their characteristics into several reduced factors. Thus conclusions are easier to determine.

The methods used to reduce the data are Principal Component Analysis, Canonic Correlation Analysis, Factor Analysis, Discriminant Analysis, Cluster Analysis, and Correspondence Analysis [5]. In addition, there are other methods for reducing data, including methods of Discriminant Analysis, Classification Analysis, Multivariate Regression, Canonical Correlation, Principal Component Analysis, Factor Analysis, Cluster Analysis, and Graphical Procedures. In this analysis, most of the information, measured in total variance, is stored in only a few of them. Previous studies show that PCA gives better results compared to other methods. This method can be used to reduce the number of dimensions and retain most of the information in the original data, as well as increasing the analysis accuracy [6], [7], [8], [9]. Based on the previous explanation, this study was conducted to determine the online learning challenges during the COVID-19 pandemic at the University of Mataram using Principal Component Analysis.

## RESEARCH METHODS

This study used the Principal Component Analysis (PCA) method. PCA is a reliable technique for extracting the structure of a data set with quite a lot of dimensions. Due to the current COVID19 situation, the survey was conducted online using Google Form and Social Media as a medium for distributing questionnaires. Students from the Faculty of Mathematics and Natural Sciences of the University of Mataram were asked to fill out a survey. The survey was conducted on students who took online classes during the pandemic. Details about the survey were shared with respondents. Completion of the survey was taken as a form of consent to participate. The average time needed to answer the questionnaire was 15 minutes. The answer choices consist of very inhibited, hampered, average, not hampered, and very uninhibited. Data collection in this study was obtained from the results of filling out questionnaires by the research sample with 15 variables related to the challenges of online learning.

The population in this study was taken from students of the Faculty of Mathematics and Natural Sciences, the University of Mataram in the class of 2016 – 2019 with 4 different study programs (Department of Mathematics, Physics, Chemistry, and Biology). The population number is 1143 students with the number in each study program, namely 280 students of the Department of Mathematics, 287 students of the Department of Chemistry, 278 students of the Department of Physics, and 298 students of the Department of Biology. Cluster sampling was done using simple random sampling in each cluster.

The questions contained in the questionnaire need to be validated and tested for reliability. Validation tests are carried out to determine the extent to which the accuracy and accuracy of the questions or variables in this stud. The testing technique that is often used by researchers to test the validity is using the Pearson Bivariate correlation (Pearson Moment Product). This analysis is done by correlating each variable score with the total score. The total score is the sum of all the variables. If $r_{count}$ is more than the $r_{table}$ (2-sided test with p-value 0.05), then the instrument or item-variable question has a significant correlation with the total score (declared valid).

Furthermore, the reliability test shows the extent to which the measurement results with the tool can be trusted. The measurement results must be reliable in the sense that they must have a level of consistency and stability. Reliability or reliability is the consistency of a series of measurements or a series of measuring instruments. This can be a measurement of the same measuring instrument (test with retest) that will give the same result, or for a more subjective measurement, whether two markers give similar scores. Reliability is not the same as validity. This means that a reliable measurement will measure consistently, but not necessarily measure what should be measured. The high and low reliability is empirically indicated by a number called the reliability coefficient value. High reliability is indicated by the value approaching the number 1. General agreement on reliability is considered satisfactory if 0.6.

Furthermore, at the data processing stage, the PCA method is used with the help of statistical software. The steps of the research are [4], [10], [11], [12], [13]:

1) Data collection using questionnaires, coding, and input.
2) Data testing using KMO value testing and Bartlett's test.
   Bartlett's test of sphericity is a test used to test the interdependence between variables that are indicators of a factor. This analysis intends to state that the variables in question are not correlated with one another in the population. Significance in this Bartlett's test must also show a number <0.05 so that factor analysis can be carried out. This test is used to test whether the resulting correlation matrix is an identity matrix, where the

identity matrix indicates that there is no correlation between the variables. The test used the null hypothesis that the correlation matrix is an identity matrix and the decision-making criteria will of Bartlett's test reject the null hypothesis if the value of the test statistic is larger than the critical value. This statistic is used to determine whether the existing observational data is worthy of further analysis with factor analysis or not. Anti-image correlation matrix value testing.

Moreover, the Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO-MSA) is an index that compares the magnitude of the observed correlation coefficient with the magnitude of the partial coefficient. The number generated by the KMO-MSA must be greater than 0.5 so that the factor analysis can be processed further. The table of anti-image correlation test results shows several numbers that form a diagonal, which is marked "a", which indicates the Measure of Sampling Adequacy (MSA) number of a variable. If the MSA number of a variable is below 0.5, then the variable must be removed and the variable selection is repeated.

3) Communalities testing.

Communalities show how much diversity the original variable is, and can explain at least 50% of the diversity of the original variable data. The greater the communalities, the closer the relationship between the indicators studied and the factors formed.

4) Total variance test explanation and scree plot making.

This step states the function that shows the number of variances associated with each factor. Factors that have an eigenvalue of 1 can be included in the model. Whereas, if there is a value that is less than 1, then it cannot be included in the model. Eigenvalues are the special set of scalars associated with the system of linear equations. It is mostly used in matrix equations. the eigenvalue is a scalar that is used to transform the eigenvector. The basic equation is $\mathbf{Ax} = \boldsymbol{\lambda}\mathbf{x}$, where **t**he number or scalar value **"$\boldsymbol{\lambda}$"** is an eigenvalue of **A**. In Mathematics, an eigenvector corresponds to the real non-zero eigenvalues that point in the direction stretched by the transformation whereas eigenvalue is considered as a factor by which it is stretched. In case, if the eigenvalue is negative, the direction of the transformation is negative.

5) Component matrix testing and rotated component matrix testing.

The component matrix contains coefficients used to express standard variables called factors. The factor loading coefficient explains the correlation between the original variable and the factor. A large correlation value indicates a close relationship between the factor and the original variable so that the variable can be used to form the factor.

A complex matrix, it is very difficult to interpret the factors. Therefore, factor rotation is used, in factor rotation, the matrix is transformed into a simpler form so that it is easier to interpret. The rotated component matrix shows the distribution of the extracted variables into the formed factors based on factor loading after the rotation process. The factor loading value may change after rotation. Variables that have factor loadings 0.5 are considered to have a weak contribution to the formed factor so that it must be reduced from the formed factor

6) Matrix transformation component testing and conclusion-making.

The higher it is the correlation value on the diagonal line, the closer the correlation between the resulting factors.

## RESULTS AND DISCUSSION

Based on the normality test and factor test that have been carried out, the following results related to the sampling adequacy and sphericity tests were obtained, related to the 15 variables used. The KMO and Bartlett's tests are useful for determining the feasibility of a variable so that it can be further processed using other advanced analyses. Based on Table 1, the KMO-MSA value is 0.826, which is greater than 0.500, and the p-value of Barlett's test of sphericity is 0.000, which is less than the significance level used (5%). Therefore, the factor analysis in this study can be continued because it meets the requirements.

**TABLE 1.** Kaiser-Meyer-Olkin and Bartlett's Test of Sphericity

| **Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy (MSA)** | | 0.826 |
| --- | --- | --- |
| **Bartlett's Test of Sphericity** | Approx. Chi-Square | 1528.237 |
| | Degree of freedom | 105.000 |
| | p-value | 0.000 |

Furthermore, Table 2 represents the anti-image matrix obtained. Based on Table 2, there is a diagonal "a" which has a value of > 50%, which indicates the Measure of Sampling Adequacy (MSA) number of a variable. The MSA values obtained are greater than 0.5, and no variable must be removed. Therefore, there is no expenditure or repetition of variables. In this case, each question given has been correlated as expected. The MSA values acquired, written in Table 3, along with the communalities.

**TABLE 2.** Anti-image Matrices

| | | P1 | P2 | P3 | P4 | P5 | P6 | P7 |
|---|---|---|---|---|---|---|---|---|
| **Anti-image Covariance** | **P1** | 0.559 | -0.246 | -0.063 | -0.135 | -0.027 | -0.019 | -0.037 |
| | **P2** | -0.246 | 0.574 | -0.027 | -0.070 | 0.034 | -0.071 | 0.007 |
| | **P3** | -0.063 | -0.027 | 0.773 | -0.083 | -0.031 | -0.144 | -0.001 |
| | **P4** | -0.135 | -0.070 | -0.083 | 0.715 | -0.062 | -0.094 | 0.033 |
| | **P5** | -0.027 | 0.034 | -0.031 | -0.062 | 0.599 | -0.065 | -0.197 |
| | **P6** | -0.019 | -0.071 | -0.144 | -0.094 | -0.065 | 0.756 | -0.029 |
| | **P7** | -0.037 | 0.007 | -0.001 | 0.033 | -0.197 | -0.029 | 0.596 |
| | **P8** | 0.050 | 0.012 | -0.039 | -0.030 | -0.093 | 0.031 | -0.219 |
| | **P9** | -0.058 | -0.036 | -0.113 | -0.071 | -0.063 | 0.054 | 0.018 |
| | **P10** | 0.002 | -0.063 | -0.032 | 0.017 | -0.032 | -0.019 | 0.012 |
| | **P11** | -0.014 | 0.010 | -0.042 | -0.041 | -0.004 | -0.069 | 0.036 |
| | **P12** | -0.024 | -0.086 | 0.045 | 0.067 | -0.008 | -0.022 | 0.080 |
| | **P13** | 0.044 | -0.058 | 0.088 | 0.041 | -0.156 | -0.059 | 0.026 |
| | **P14** | -0.058 | -0.008 | -0.020 | -0.032 | 0.048 | -0.034 | -0.094 |
| | **P15** | -0.018 | -0.037 | 0.035 | -0.010 | -0.004 | -0.075 | -0.021 |
| **Anti-image Correlation** | **P1** | 0.812[a] | -0.435 | -0.095 | -0.214 | -0.047 | -0.030 | -0.064 |
| | **P2** | -0.435 | 0.823[a] | -0.041 | -0.109 | 0.058 | -0.108 | 0.013 |
| | **P3** | -0.095 | -0.041 | 0.863[a] | -0.111 | -0.046 | -0.188 | -0.002 |
| | **P4** | -0.214 | -0.109 | -0.111 | 0.875[a] | -0.095 | -0.128 | 0.050 |
| | **P5** | -0.047 | 0.058 | -0.046 | -0.095 | 0.829[a] | -0.097 | -0.330 |
| | **P6** | -0.030 | -0.108 | -0.188 | -0.128 | -0.097 | 0.883[a] | -0.043 |
| | **P7** | -0.064 | 0.013 | -0.002 | 0.050 | -0.330 | -0.043 | 0.750[a] |
| | **P8** | 0.088 | 0.021 | -0.059 | -0.047 | -0.160 | 0.048 | -0.376 |
| | **P9** | -0.094 | -0.057 | -0.156 | -0.102 | -0.099 | 0.076 | 0.028 |
| | **P10** | 0.003 | -0.096 | -0.043 | 0.023 | -0.047 | -0.025 | 0.017 |
| | **P11** | -0.022 | 0.014 | -0.054 | -0.054 | -0.005 | -0.089 | 0.053 |
| | **P12** | -0.037 | -0.132 | 0.059 | 0.092 | -0.011 | -0.029 | 0.120 |
| | **P13** | 0.067 | -0.088 | 0.115 | 0.056 | -0.231 | -0.078 | 0.039 |
| | **P14** | -0.093 | -0.012 | -0.027 | -0.045 | 0.075 | -0.047 | -0.146 |
| | **P15** | -0.028 | -0.057 | 0.046 | -0.014 | -0.006 | -0.099 | -0.031 |

**TABLE 2.** (Continued)

| | | P8 | P9 | P10 | P11 | P12 | P13 | P14 | P15 |
|---|---|---|---|---|---|---|---|---|---|
| **Anti-image Covariance** | **P1** | 0.050 | -0.058 | 0.002 | -0.014 | -0.024 | 0.044 | -0.058 | -0.018 |
| | **P2** | 0.012 | -0.036 | -0.063 | 0.010 | -0.086 | -0.058 | -0.008 | -0.037 |
| | **P3** | -0.039 | -0.113 | -0.032 | -0.042 | 0.045 | 0.088 | -0.020 | 0.035 |
| | **P4** | -0.030 | -0.071 | 0.017 | -0.041 | 0.067 | 0.041 | -0.032 | -0.010 |
| | **P5** | -0.093 | -0.063 | -0.032 | -0.004 | -0.008 | -0.156 | 0.048 | -0.004 |
| | **P6** | 0.031 | 0.054 | -0.019 | -0.069 | -0.022 | -0.059 | -0.034 | -0.075 |
| | **P7** | -0.219 | 0.018 | 0.012 | 0.036 | 0.080 | 0.026 | -0.094 | -0.021 |
| | **P8** | 0.568 | -0.066 | -0.023 | -0.109 | -0.055 | -0.117 | -0.057 | 0.031 |
| | **P9** | -0.066 | 0.678 | -0.008 | -0.053 | -0.149 | -0.085 | 0.020 | -0.080 |
| | **P10** | -0.023 | -0.008 | 0.744 | -0.110 | -0.069 | -0.012 | -0.154 | -0.101 |
| | **P11** | -0.109 | -0.053 | -0.110 | 0.781 | -0.120 | 0.040 | -0.044 | -0.001 |
| | **P12** | -0.055 | -0.149 | -0.069 | -0.120 | 0.738 | -0.014 | 0.044 | -0.135 |
| | **P13** | -0.117 | -0.085 | -0.012 | 0.040 | -0.014 | 0.757 | -0.112 | 0.040 |
| | **P14** | -0.057 | 0.020 | -0.154 | -0.044 | 0.044 | -0.112 | 0.699 | -0.150 |
| | **P15** | 0.031 | -0.080 | -0.101 | -0.001 | -0.135 | 0.040 | -0.150 | 0.751 |
| **Anti-image Correlation** | **P1** | 0.088 | -0.094 | 0.003 | -0.022 | -0.037 | 0.067 | -0.093 | -0.028 |
| | **P2** | 0.021 | -0.057 | -0.096 | 0.014 | -0.132 | -0.088 | -0.012 | -0.057 |
| | **P3** | -0.059 | -0.156 | -0.043 | -0.054 | 0.059 | 0.115 | -0.027 | 0.046 |
| | **P4** | -0.047 | -0.102 | 0.023 | -0.054 | 0.092 | 0.056 | -0.045 | -0.014 |
| | **P5** | -0.160 | -0.099 | -0.047 | -0.005 | -0.011 | -0.231 | 0.075 | -0.006 |
| | **P6** | 0.048 | 0.076 | -0.025 | -0.089 | -0.029 | -0.078 | -0.047 | -0.099 |
| | **P7** | -0.376 | 0.028 | 0.017 | 0.053 | 0.120 | 0.039 | -0.146 | -0.031 |
| | **P8** | 0.809[a] | -0.107 | -0.036 | -0.164 | -0.085 | -0.178 | -0.090 | 0.048 |
| | **P9** | -0.107 | 0.878[a] | -0.011 | -0.072 | -0.210 | -0.118 | 0.030 | -0.113 |
| | **P10** | -0.036 | -0.011 | 0.887[a] | -0.144 | -0.094 | -0.016 | -0.214 | -0.135 |
| | **P11** | -0.164 | -0.072 | -0.144 | 0.877[a] | -0.158 | 0.052 | -0.060 | -0.001 |
| | **P12** | -0.085 | -0.210 | -0.094 | -0.158 | 0.799[a] | -0.019 | 0.062 | -0.182 |
| | **P13** | -0.178 | -0.118 | -0.016 | 0.052 | -0.019 | 0.785[a] | -0.155 | 0.053 |
| | **P14** | -0.090 | 0.030 | -0.214 | -0.060 | 0.062 | -0.155 | 0.850[a] | -0.207 |
| | **P15** | 0.048 | -0.113 | -0.135 | -0.001 | -0.182 | 0.053 | -0.207 | 0.856[a] |

Table 3 below represents the MSA score obtained from the anti-image correlation in Table 2, along with the communalities.

**TABLE 3.** MSA Score and Communalities

| No. | Factors | MSA Value | *Extraction* |
|---|---|---|---|
| 1 | Lack of concentration | 0.812 | 0.615 |
| 2 | Lack of material understanding | 0.823 | 0.566 |
| 3 | No direct discussion | 0.863 | **0.434** |
| 4 | Unconcern (boredom) | 0.875 | 0.545 |
| 5 | Lack of facilities | 0.829 | 0.612 |
| 6 | Lack of study companion | 0.883 | **0.364** |
| 7 | Inadequate network | 0.750 | 0.631 |
| 8 | Insufficient electricity | 0.809 | 0.644 |
| 9 | Platform differences | 0.878 | **0.390** |
| 10 | Household chores | 0.887 | **0.436** |
| 11 | Organization activity | 0.877 | **0.322** |
| 12 | Lots of assignments | 0.799 | 0.545 |
| 13 | Lack of technology mastery | 0.785 | **0.396** |
| 14 | Environmental conditions | 0.850 | **0.359** |
| 15 | Uncertain learning schedules | 0.856 | **0.444** |

Based on Table 3, the MSA values for all the variables studied are greater than 0.5. Therefore, all variables are eligible for factor analysis. Table 3 also shows that the extraction values for the variable are greater than 0.5, except for variable 3, variable 6, variable 9, variable 10, variable 11, variable 13, and variable 15.

Moreover, Table 4 shows the total variance explained, along with the percentage of cumulative. Based on Table 4, three factors can be formed from the 15 variables analyzed. The condition is that the eigenvalues are more than 1. The eigenvalue of component 1 is 4.344, and it becomes factor 1. It can explain 28.957% of the variation. Similar explanations go for the other components.

**TABLE 4.** Total Variance Explained

| Component | Initial Eigenvalues | | | *Extraction Sums of Squared Loadings* | | | *Rotation Sums of Squared Loadings* | | |
|---|---|---|---|---|---|---|---|---|---|
| | Total | % of Variance | % Cumulative | Total | % of Variance | % Cumulative | Total | % of Variance | % Cumulative |
| 1 | 4.344 | 28.957 | 28.957 | 4.344 | 28.957 | 28.957 | 2.492 | 16.610 | 16.610 |
| 2 | 1.719 | 11.462 | 40.418 | 1.719 | 11.462 | 40.418 | 2.444 | 16.295 | 32.905 |
| 3 | 1.238 | 8.253 | 48.671 | 1.238 | 8.253 | 48.671 | 2.365 | 15.766 | 48.671 |
| **4** | 0.994 | 6.626 | 55.297 | | | | | | |
| 5 | 0.924 | 6.161 | 61.458 | | | | | | |
| 6 | 0.788 | 5.251 | 66.708 | | | | | | |
| 7 | 0.752 | 5.014 | 71.722 | | | | | | |
| 8 | 0.709 | 4.730 | 76.452 | | | | | | |
| 9 | 0.666 | 4.441 | 80.893 | | | | | | |
| 10 | 0.613 | 4.089 | 84.982 | | | | | | |
| 11 | 0.534 | 3.562 | 88.544 | | | | | | |
| 12 | 0.495 | 3.297 | 91.841 | | | | | | |
| 13 | 0.475 | 3.169 | 95.010 | | | | | | |
| 14 | 0.377 | 2.513 | 97.523 | | | | | | |
| 15 | 0.372 | 2.477 | 100.000 | | | | | | |

The eigenvalues obtained in Table 4 are represented in a scree plot (Figure 1). The scree plot can also show the number of factors formed. It can be seen that three-component points have eigenvalues > 1, which means that there are three factors formed.

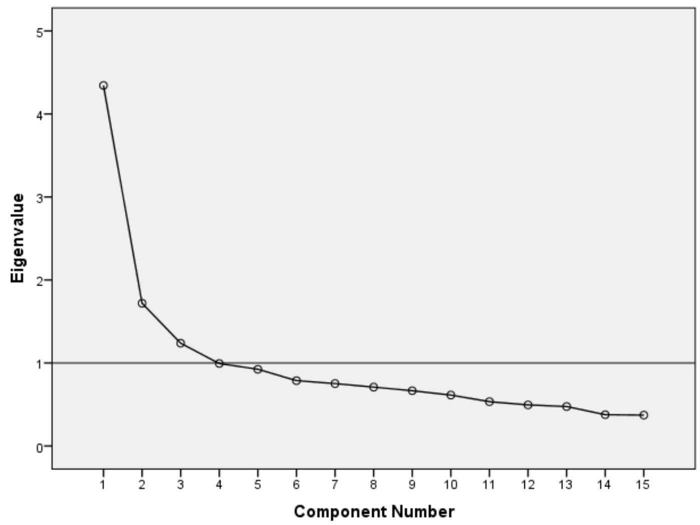


**FIGURE 1.** Scree Plot

Table 5 below indicated the matrix components before and after being rotated, to make them easier to interpret. The matrix component in Table 5 represents the correlation value between each variable and the formed factors. Based on the results obtained, variables that have greater factor loadings will be included in the formed factors.

**TABLE 5.** Matrix Components and Rotated Matrix Components

| No. | Factors | Component | | | Rotated Component | | |
|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 1 | 2 | 3 |
| 1 | Lack of concentration | 0.612 | -0.406 | -0.274 | **0.735** | 0.004 | 0.273 |
| 2 | Lack of material understanding | 0.608 | -0.427 | -0.117 | **0.639** | -0.030 | 0.395 |
| 3 | No direct discussion | 0.488 | -0.173 | -0.407 | **0.641** | 0.147 | 0.032 |
| 4 | Unconcern (boredom) | 0.540 | -0.248 | -0.437 | **0.726** | 0.115 | 0.062 |
| 5 | Lack of facilities | 0.577 | 0.502 | -0.166 | 0.234 | **0.743** | 0.071 |
| 6 | Lack of study companion | 0.541 | -0.127 | -0.236 | **0.541** | 0.198 | 0.179 |
| 7 | Inadequate network | 0.484 | 0.600 | -0.190 | 0.150 | **0.779** | -0.030 |
| 8 | Insufficient electricity | 0.571 | 0.562 | 0.033 | 0.074 | **0.773** | 0.200 |
| 9 | Platform differences | 0.611 | -0.070 | 0.108 | 0.334 | 0.253 | **0.463** |
| 10 | Household chores | 0.544 | -0.084 | 0.365 | 0.131 | 0.183 | **0.620** |
| 11 | Organization activity | 0.502 | -0.073 | 0.254 | 0.173 | 0.181 | **0.509** |
| 12 | Lots of assignments | 0.454 | -0.251 | 0.526 | 0.047 | -0.020 | **0.737** |
| 13 | Lack of technology mastery | 0.421 | 0.444 | 0.145 | -0.037 | **0.584** | 0.230 |
| 14 | Environmental conditions | 0.570 | 0.099 | 0.156 | 0.201 | 0.370 | **0.426** |
| 15 | Uncertain learning schedules | 0.505 | -0.221 | 0.375 | 0.162 | 0.046 | **0.645** |

Through rotated matrix components in Table 5, it can be seen that a variable enters Factor 1, Factor 2, or Factor 3, namely by looking at the greatest value of the three existing factors. The analysis resulted in the following.

a. Variables that belong to the group of Factor 1 are lack of concentration, material understanding, not direct discussion, unconcern (boredom), and lack of study companion variables.
b. Variables that belong to the group of Factor 2 are lack of facilities, inadequate network, insufficient electricity, and lack of technological mastery variables.
c. Variables that belong to the group of Factor 3 are platform differences, household chores, organizational activities, lots of assignments, environmental conditions, and uncertain learning schedules variables.

The following table shows the results for components of matrix transformation obtained.

**TABLE 6.** Components of Matrix Transformation

| Component | 1 | 2 | 3 |
|---|---|---|---|
| 1 | 0.610 | 0.527 | 0.592 |
| 2 | -0.450 | 0.845 | -0.289 |
| 3 | -0.652 | -0.090 | 0.753 |

Table 6 shows the correlation value of each factor/ component. In Component 1, the correlation value is 0.610 > 0.500; in Component 2, the correlation value is 0.845 > 0.500, and in Component 3, the correlation value is 0.753 > 0.500. Since all correlation values are greater than 0.5, these three factors can be concluded worthy to summarize the 15 variables analyzed. Component transformation matrix indicates the magnitude correlation between components or factors that are formed. The higher it is the correlation value on the diagonal line, the closer the correlation between the resulting factors.

## CONCLUSION

Of the fifteen variables observed, three factors were obtained. The dominant factor is Factor 1, since it has an eigenvalue of 4.344 and can explain 28.957% of the variation. The variables included in factor 1 are the variables that most hinder online lectures, namely the lack of concentration, material understanding, not direct discussion, unconcern (boredom), and lack of study companion variables. The results obtained can be used as a consideration to maximize online lectures during the COVID-19 pandemic.

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