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Analysis of Students Performance in Mathematics before and during Covid-19 Pandemic using PageRank: A Preliminary Study

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Abstract

In a normal situation, a university is constantly utilizing standard statistical analysis tools to provide a student's ranking through their academic achievement. The tools provides analysis of pairwise comparison among students on their academic performance but unfortunately visualization of the results is limited to the use of line graph, histogram, tables and boxplot which are not easily explained. In this study, another way of analyzing the pairwise comparison of academic performance on Mathematics among students is introduced that is by using interaction graph which is based on a weighted directed graph approach. The ranking of student's performance in Mathematics is calculated using Page Rank (PR) algorithm. A sample of final examination result for twenty-one students whom enrolled in Mathematics courses in Fakulti Sains Komputer dan Matematik (FSKM), UiTM Shah Alam are investigated. Their performance by marks in two Mathematics courses taken before the pandemic and three Mathematics courses taken during the pandemic are analyzed. The graph with twenty-one nodes represent the students, while the directed links between two students represent the Mathematics relative performance is established. The rank of the students' Mathematics performance is obtained from PR value of the graph. The largest PR value indicates the highest performance of the respective student. The result revealed that 62 percent of the students have shown better Mathematics performance even though the learning platforms before and during Covid-19 pandemic were drastically changed. Although this result does not indicate the whole picture of FSKM students' Mathematics performance, it gives a good insight to the academic administrator in making better decision. Besides, the interaction graph provides an easy way to explain the result only by looking into the graph.

Keywords PageRank, Directed Graph, Mathematics Performance, Ranking

INTRODUCTION

The coronavirus Covid-19 outbreak disrupted the human life starting the end of year 2019. As in any other sectors, the pandemic has affected education industries in many ways. All government actions taken are focused on a common goal of reducing the spread of coronavirus by introducing measures that limit social contact. Many countries have suspended face-to-face teaching and exams, as well as placing strict restrictions on immigration which eventually affecting students. Where possible, traditional classes are being replaced with electronic books and materials, while various e-learning platforms have emerged which enable virtual interaction between teachers and students. In many cases, the national television channels and social media platforms are being utilized for the national education

(Gonzalez et al., 2020). These sudden changes in the educational context have created uneasiness among all educators who are basically worried that this new norms might affect the student academic performances. However the nightmare is proven and showed that the student academic performance are declining during pandemic in many courses such as in Mathematics (Syerrina, Siti Madhihah and Nazihah; 2021), among veterinary medical students (Mahdy; 2020) and among Afghans' students (Aminuddin; 2021). There is abundant literature looking at factors that affect student performance (Hanson, 2000; Simmons et al., 2005; Garton et al., 2000; Mckenzie and Schweitzer, 2001) which stated that academic performance is the most critical determinants of university performance. In short, student performance can be regarded as an important aspect that needs to be emphasized by the universities leader because it is a significant indicator of a university's performance. With the existence of Covid-19 pandemic, this student performance indicator, especially student academic performance, has become very useful to help educators in reshaping future educational materials and assessments. Therefore, by knowing students' academic performance before and during the pandemic, the education administrators or leaders could get some valuable insights to make decisions in the educational context due to the health crisis.

In normal situation, the academic administrators normally utilize standard statistical tools such as Minitab, SPSS and excel or by using only descriptive and inferential statistical analysis to analyze student's achievement by means of the student ranking. The tools could also provide the analysis of pairwise comparison among students on their academic performance but unfortunately visualization of the results is limited to the use of line graph, histogram, tables and boxplot which are not easily explained. Thus, this study offers another method to determine the students' ranking that is by using graph theory. In this approach, data is transformed into graph. The graphs or networks are often used to represent a network structure, with vertices (or nodes) represent people and edges (or connections) represent interactions between pairs of vertices (or nodes). The network method is not only excellent in simplifying and visualizing massive quantity of data, but it is also extremely good at identifying the essential components and connections. Furthermore, various methods for evaluating and ranking people based on their position and function in the underlying graph which reflecting the bilateral connections between them can easily be created. One of the ways to calculate the individual ranking based on the interaction graph is by using a well-known PageRank (PR) algorithm. PR algorithm was initially introduced by Page and Brin (1998) to find the importance of web page based on link structure but eventually used in solving other real life problems involving ranking. Here, the graph's vertices are rated according to their centrality in a diffusion process on the network.

In this preliminary study, the PR method is explored to analyse and rank the student's performance in Mathematics through a weighted directed graph of the student network. A small group of twenty-one students in third semester and enrolled in Mathematics course in FSKM, UiTM Shah Alam are involved in this study in which their academic performance by marks in two Mathematics courses taken before pandemic and three Mathematics courses taken during the pandemic are analysed. Therefore, there is no generalization of Mathematics performance to all Mathematics students of FSKM can be made due to small sample size involved in this study. The graphs with twenty-one nodes represent the students, while the directed links between two students represent the Mathematics relative performance. The rank of the students' Mathematics performance which obtained from the PR value of the graph is subsequently represented in the graph network which created a different way of visualizing the students' performance.

METHODS

Several steps are involved in this study in which the procedures are presented below.

Step 1: Data Collection

The dataset in this study is the final assessment marks for selected courses. Here, the students are ensured to fulfil certain conditions as below:

i) The students are in the same group class for the specified Mathematics courses where the lecturer who teach is unchanged.

ii) The students are not in a "repeat" status for every specified Mathematics courses.

Step 2: Development of student network graph

In this step, the network graph of academic performance of the students is constructed. Let $\boldsymbol{G}(\boldsymbol{V},\boldsymbol{E})$ defines the graph network, such that $\boldsymbol{V}(\boldsymbol{G}) = \{\boldsymbol{S}_1, \boldsymbol{S}_2, \boldsymbol{S}_3\}$ where $\boldsymbol{S}_i, \boldsymbol{i} = 1,2,3$ are the students. The edge between two students exists only with assumption that the student can be compared in terms of Mathematics achievement. If given the final marks of student *i* and student *j* are $(\boldsymbol{m}_1^i,...,\boldsymbol{m}_t^i)$ and $(\boldsymbol{m}_1^j,...,\boldsymbol{m}_t^j)$, for course 1, …, *t*, then the edge weight, $\boldsymbol{w}_{ij}$ is calculated by using Eq. (1).

$$w_{ij} = \sum_{n=1}^{t} (m_n^i - m_n^j) \tag{1}$$

where $\boldsymbol{w}_{ij}$ is the edge weight that represents relative students' academic performance between student *i* and student *j*. If $\boldsymbol{w}_{ij} > 0$, then the edge is directed from vertex *j* to vertex *i* and if $\boldsymbol{w}_{ij} < 0$, the edge is directed from vertex *i* to vertex *j* and both edge is having the weight of $|\boldsymbol{w}_{ij}|$. If $\boldsymbol{w}_{ij} = 0$, then there is no edge from vertex *i* to vertex *j*. Consider Table 1 which contain information on final marks obtained by three Mathematics students for two different courses.

Table 1 Marks for two courses taken by three students

Students	Marks for course A, m_1	Marks for course B, m_2
S_1	76	45
S_2	65	34
S_3	54	56

Using Eq. (1), $\boldsymbol{w}_{ij}$ for *i*, *j* = 1, 2, 3 are calculated as follows:

$$w_{12} = (m_1^1 - m_1^2) + (m_2^1 - m_2^2) = (76-65) + (45-34) = 22$$
$$w_{13} = (m_1^1 - m_1^3) + (m_2^1 - m_2^3) = (76-54) + (45-56) = 11$$
$$w_{23} = (m_1^2 - m_1^3) + (m_2^2 - m_2^3) = (65-54) + (34-56) = -11$$

Since $w_{12} > 0$ and $w_{13} > 0$, therefore the edge is directed from vertex S_2 to vertex S_1 and from vertex S_3 to S_1 with edge weight equal to 22 and 11 respectively. In this context, since $w_{23} < 0$, therefore the edge is directed from S_2 to S_3 with edge weight equal to 11. The weighted directed graph of student's performance is obtained and illustrated in Fig.1.

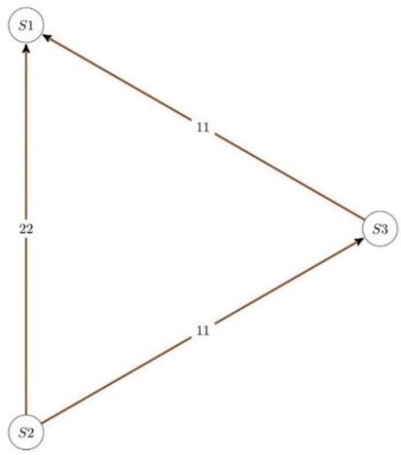

Figure 1. Weighted directed graph of students relative performance G (V,E)

Next, the graph G (V, E) is represented as adjacency matrix by using Definition 1.

Definition 1. (Adjacency matrix of weighted directed graph)

The adjacency matrix for a weighted directed graph representing relative student's academic performance *G(V,E)* is an *nxn* matrix $\boldsymbol{A} = [\boldsymbol{a}_{ij}] = \begin{bmatrix} \boldsymbol{a}_{11} & \boldsymbol{a}_{12} & \cdots \boldsymbol{a}_{1n} \\ \vdots & \vdots & \vdots \; \vdots \\ \boldsymbol{a}_{n1} & \boldsymbol{a}_{n2} & \cdots \boldsymbol{a}_{nn} \end{bmatrix}$ such that

$$a_{ij} = \begin{cases} |w_{ij}| \in \Re^+ \text{ if } e_{ij} \in E \text{ and } i \neq j \\ 0 \text{ if } e_{ij} \notin E \text{ or } i = j \end{cases} \quad \forall i, j = 1, 2, \ldots, n$$

Thus the adjacency matrix for Figure1 is as follows.

$$\boldsymbol{A} = (\boldsymbol{a}_{ij}) = \begin{pmatrix} 0 & 0 & 0 \\ 22 & 0 & 11 \\ 11 & 0 & 0 \end{pmatrix} \qquad (2)$$

Step 3: Calculation of transition probability, $\boldsymbol{p}_{ij}$

From Figure1, the transition probability matrix, $\boldsymbol{p}_{ij}$ is calculated using the Definition 2.

Definition 2. (Transition probability matrix of weighted directed graph)

The transition probability matrix for a weighted directed graph representing relative student's academic performance G(V,E) is an $n \times n$ matrix

$$\boldsymbol{P} = \boldsymbol{P}_{ij} = \begin{cases} \dfrac{\boldsymbol{w}_{ij}}{\sum_{j:i\to j} \boldsymbol{w}_{ij}} & \text{if there is an edge from } \boldsymbol{i} \text{ to } \boldsymbol{j} \\ 0 & \text{if there is no edge from i to j} \end{cases}$$

where $\boldsymbol{w}_{ij}$ is the edge weight that represent the relative students' performance between student *i* and *j* while $\sum_{j:i\to j} w_{ij}$ is the total weight of the out-going edges for vertex *i*. As for Fig.1, the calculation of the transition probability p_{ij} is as follows:

$$p_{21} = \frac{w_{21}}{w_{21} + w_{22} + w_{23}} = \frac{22}{22 + 0 + 11} = 0.6667$$
$$p_{23} = \frac{w_{23}}{w_{23} + w_{22} + w_{21}} = \frac{11}{11 + 0 + 22} = 0.3333$$
$$p_{31} = \frac{w_{31}}{w_{31} + w_{32} + w_{33}} = \frac{11}{11 + 0 + 0} = 1$$

Thus, the transition probability matrix is presented as below.

$$p_{ij} = \begin{pmatrix} 0 & 0 & 0 \\ 0.6667 & 0 & 0.3333 \\ 1 & 0 & 0 \end{pmatrix} \qquad (4)$$

Step 4: Check for stochasticity of the transition probability matrix $\boldsymbol{P_{ij} = 0}$

The matrix in Eq. (4) must be stochastic whereby there are always at least one incoming link into every vertex in the corresponding graph, so that every row in the matrix are non-zero rows. If it is not, then proceed to Step 5. If yes, then proceed to Step 6.

Step 5: Find the revised transition probability matrix, $\overline{\boldsymbol{p}}_{ij}$

From Eq. (4), all zeroes in the first row are replaced using the Eq. (5).

$$\frac{1}{n}\cdot \mathrm{e}^{T} \tag{5}$$

The formula shows that $\boldsymbol{e}^{T}$ is the row vector of all element are ones and n is the order of $\boldsymbol{p}_{ij}$. As for Eq. (4), the first row is replaced by $\frac{1}{\boldsymbol{n}}\bullet \boldsymbol{e}^{T} = \frac{1}{3}(1,1,1) = (0.3333, 0.3333, 0.3333)$. Then, the revised transition probability matrix, $\overline{\boldsymbol{p}}_{ij}$ is produced and shown in Eq. (6).

$$\overline{\boldsymbol{p}}_{ij} = \begin{pmatrix} 0.3333 & 0.3333 & 0.3333 \\ 0.6667 & 0 & 0.3333 \\ 1 & 0 & 0 \end{pmatrix} \tag{6}$$

Step 6: Develop transposed of the transition probability matrix, $(\boldsymbol{p}_{ij})^{T}$ or $(\overline{\boldsymbol{p}}_{ij})^{T}$

Eq. (7) is the transposed of Eq. (6).

$$\left(\overline{\boldsymbol{p}}_{ij}\right)^{T} = \begin{pmatrix} 0.3333 & 0.6667 & 1 \\ 0.3333 & 0 & 0 \\ 0.3333 & 0.3333 & 0 \end{pmatrix} \tag{7}$$

Step 7: Calculate the PageRank value for each node, *PR*(*i*)

The PageRank value, *PR*(*i*) is calculated using Eq. (8).

$$PR(i) = \begin{cases} \dfrac{1-\mathrm{d}}{\mathrm{n}} + \mathrm{d}\displaystyle\sum_{\mathrm{j:j\to i}} \left(\bar{\mathrm{p}}_{\mathrm{ij}}\right)^{\mathrm{T}} \cdot \mathrm{PR(j)}\,,\text{for } \forall\ \mathrm{i} \text{ and Step 5 is considered} \\ \dfrac{1-\mathrm{d}}{\mathrm{n}} + \mathrm{d}\displaystyle\sum_{\mathrm{j:j\to i}} \left(\mathrm{p}_{\mathrm{ij}}\right)^{\mathrm{T}} \cdot \mathrm{PR(j)}\,,\text{for } \forall\ \mathrm{i} \text{ and Step 5 is skipped} \end{cases} \tag{8}$$

The constant *d* refers to the damping factor which is fixed at 0.85 while *n* refers to the number of nodes involved in the graph. In this example, let the initial *PR*(*i*) for i = 1, 2, 3 equals to $\frac{1}{3}$ and is shown in Eq.(9).

$$\begin{bmatrix} PR(S1) \\ PR(S2) \\ PR(S3) \end{bmatrix} = \begin{bmatrix} 0.3333 \\ 0.3333 \\ 0.3333 \end{bmatrix} \tag{9}$$

By using Eq. (9) as initial PR values for vertex *i* where *i* = 1, 2, 3 for zeros' iteration, the next value of *PR(i)* for *i* = 1, 2, 3 is iterated and presented in Table 2.

Table 2. PageRank value of each node by iterations

Iteration	Node		
	S_1	S_2	S_3
1	0.6167	0.1444	0.2389
2	0.5096	0.2247	0.2656
⋮	⋮	⋮	⋮

9	**0.5379**	**0.2024**	**0.2597**
10	**0.5379**	**0.2024**	**0.2597**

The PR value for the 10th iteration from Table 2 is shown in the form of Eq. (14).

$$\begin{bmatrix} \mathrm{PR(S1)} \\ \mathrm{PR(S2)} \\ \mathrm{PR(S3)} \end{bmatrix} = \begin{bmatrix} 0.5379 \\ 0.2024 \\ 0.2597 \end{bmatrix} \tag{14}$$

Step 8: Use the value of PageRank to rank the nodes.
The PR value corresponds to how much significant the performance of each student. The higher the value of PR, the better the student's academic performance is. The percentage for each value of node is shown in Eq. (15).

$$\begin{bmatrix} \mathrm{PR(S1)} \\ \mathrm{PR(S2)} \\ \mathrm{PR(S3)} \end{bmatrix} = \begin{bmatrix} 0.5379 \\ 0.2024 \\ 0.2597 \end{bmatrix} = \begin{bmatrix} 53.79\% \\ 20.24\% \\ 25.97\% \end{bmatrix} \tag{15}$$

The highest percentage is 53.79% which corresponds to node S_1. It is followed by node S_3 with 25.97% and finally, node S_2 with 20.24%. The students are ranked from high to low in order as S_1, S_3, and S_2 according to their academic performance. Therefore, it can be concluded that student S_1 performs academically very well, as compared to the other students.

RESULT AND DISCUSSION

Twenty-one Mathematics students from third semester whose study at FSKM, UiTM Shah Alam who fulfilled certain criteria explained in Section 2 are involved in the study. The final assessment marks obtained by the students in three distinct Mathematics courses namely Numerical Method, Mathematics Method and Calculus before and during pandemic are identified and analysed. The set of student is represented as $\boldsymbol{V} = \{\boldsymbol{S}_1, \boldsymbol{S}_2, ..., \boldsymbol{S}_{21}\}$ and the set of edge connecting S_i and S_j represents the comparability in terms of Mathematics achievement between student-i and student-j and this is represented as $\boldsymbol{E} = \{(\boldsymbol{S}_i, \boldsymbol{S}_j);\, \boldsymbol{i}, \boldsymbol{j} = 1, 2, ..., 21\}$. The weight of the edge is then calculated which later is used to indicates the direction of the edge in the graph. The weighted directed graphs which represent the student relative performance before and during pandemic are illustrated in Figure 2 and Figure 3.

Fig.2. Weighted directed graph of students relative performance during the pandemic

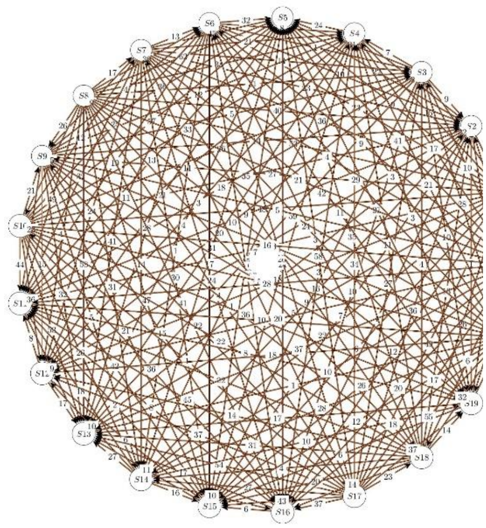

Fig.3. Weighted directed graph of students relative performance before the pandemic

Following the procedures discussed in Section 2, the PR value for each student before and during pandemic and their differences are calculated and presented in Table 3.

Table 3 Students and their PageRank percentage differences

No	Student	PR value (%) before pandemic	PR value (%) during pandemic	PR value difference (%)
1.	S_1	6.25%	29.80%	23.55%
2.	S_2	2.84%	1.97%	-0.87%
3.	S_3	2.26%	2.66%	0.40%
4.	S_4	2.68%	2.09%	-0.60%
5.	S_5	28.62%	2.76%	-25.85%
6.	S_6	2.22%	3.14%	0.92%
7.	S_7	1.97%	2.12%	0.14%
8.	S_8	1.87%	2.24%	0.37%
9.	S_9	2.10%	5.09%	2.99%
10.	S_{10}	1.89%	2.18%	0.30%
11.	S_{11}	4.70%	1.97%	-2.74%
12.	S_{12}	2.95%	2.43%	-0.52%
13.	S_{13}	9.52%	3.29%	-6.22%
14.	S_{14}	2.26%	2.53%	0.27%
15.	S_{15}	4.15%	2.66%	-1.49%

16.	S_{16}	2.95%	6.09%	3.14%
17.	S_{17}	1.88%	1.92%	0.04%
18.	S_{18}	2.13%	3.29%	1.17%
19.	S_{19}	2.95%	10.49%	7.54%
20.	S_{20}	11.79%	9.19%	-2.59%
21.	S_{21}	2.02%	2.07%	0.05%

Table 3 shows that before the pandemic, the highest PR value percentage is 28.62% which corresponds to student S_5. It is followed by student S_{20} with 11.79%, student S_{13} with 9.52% and student S_1 with 6.25%. The lowest percentage is 1.87% which corresponds to student S_8. Therefore, before the pandemic, student S_5 is the most successful student and student S_8 is the least successful student, respectively. On the other hand, during the pandemic, student S_1 is the most successful student due to largest PR value 29.80% and student S_{11} is the least successful student with PR value 1.92%, respectively.

In addition to this, thirteen students have a positive PR percentage difference, while another eight students have a negative PR percentage difference. This implies that 62% of the students who gain a positive PR percentage difference are the students who could increase and maintain their academic performance during the pandemic. They are able to continue to excel in their study as in normal situation and maintain the same momentum to survive during the pandemic. For example, student S_1 increased the PR percentage from 6.25% to 29.80%, which is a 23.55% difference, which put him into the top-tier. The other twelve students managed to increase the PR percentage during the pandemic. These students have potential to get through their studies even though being in pandemic situation.

On the other hand, there are eight students (38%) have a negative PR percentage difference. They could be indicated as more likely to be incapable of increasing and maintaining their academic performance during the pandemic. They are also unable to continue their study as in normal situation and are not able to adapt with the pandemic situation. For example, student S_5 has recorded a decline in his/her PR percentage from 28.62% to 2.76%, which is a 25.85% difference, which eventually put the student into the rank number ten. Even though the decrease of the PR percentage difference is relatively small, this can also indicate that their performance have worsens during the pandemic. This situation might be due to certain factors such as learning style, virtual class environment, internet connection problems or any personal problems.

The ranking of student which are represented by a node in the graph are further visualized in Figure 4 and Figure 5. The larger the size of the node which represent the bigger PR value denotes that the student performed better in the selected Mathematics courses, as compared to the other students.

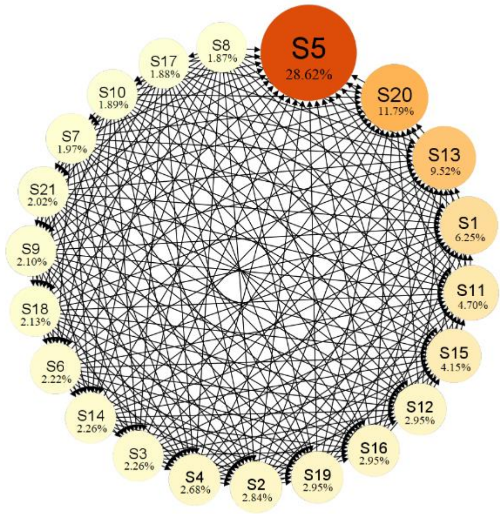

Fig.4. PR value (%) for each node before pandemic.

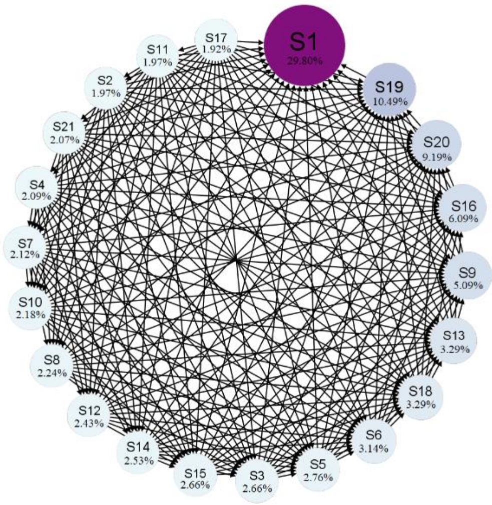

Fig.5. PR value (%) for each node during pandemic.

As an example, the size of node S_5 in Fig.4 is bigger than node S_5 in Fig.5. This indicates that the PR percentage value decreases when pandemic occurs. In addition, the size of node S_1 in Fig.4 is smaller than node S_1 in Fig.5, which denotes that the PR percentage value increases when pandemic situation arrived. This type of visualisation using graph is capable to give information on the performance of particular student during the pandemic by means of the size of the nodes. With this valuable insights, appropriate actions could be planned ahead to boost the students' academic performance.

CONCLUSION

This study has successfully utilised the PageRank method and applied graph theory to study the students' performance in Mathematics before and during Covid-19 pandemic. The result shows that 62% of the students have increased their performance in the selected Mathematics courses while 38% of the student could not able to maintain their excellence in Mathematics achievement during the pandemic. This study shows that the PageRank method has a great potential to be used as an analysis tool besides the commonly used statistical tool. The beautiful part of using PageRank method is that the outcomes can be visualized by graph and the results are very easily interpreted. However, the result cannot be generalize to the whole population of Mathematics performance of FSKM students due the small sample size of student engaged in the study. Therefore it is a need to increase the sample size of the students in the similar study so that the result obtained will be more meaningful for the administrator to implement some changes in teaching and learning during Covid-19.

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