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Analyzing the Impact of the Pandemic on Indonesia's Economic Growth Using Dynamic Time Warping

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ABSTRACT

Asia's GDP experienced the most drastic decline during the COVID-19 compared to other economic crises. This study collected data on economic indicators for each province/city to observe economic growth in Indonesia, such as Gross Regional Domestic Product (GRDP), unemployment rate, and economic growth. The clustering method on time series data found several provinces/cities with similar economic growth patterns to observe the pandemic's impact on their economies. Knowing the pattern of economic growth will help the regulation holder support provinces with the right policy. For this purpose, we utilized the Dynamic Time Warping (DTW) distance with the k-medoids procedure. The DTW is an algorithm for measuring the similarity between two temporal sequences. The clustering of the three economic indicators had three clusters with the most optimal validation index. Each cluster had almost the same pattern since the trend tended to increase from before the pandemic and then decrease during the pandemic. The decrease in GRDP was less significant than the minimal data on GRDP that happened before the pandemic. Most provinces had negative economic growth during the pandemic, which skyrocketed even for the first quarter of 2023, almost the same as before the pandemic.

1. Introduction

The 1997 until 1998 Asian economic crisis and the 2008 global economic crisis resulted in shallow Gross Domestic Product (GDP) growth in the Asian region, with growth rates of 1.3% and 4.7%, respectively. On top of that, the COVID-19 outbreak in 2000 caused economic growth to almost zero. Based on an analysis reported by the International Monetary Fund (IMF) in April 2020, apart from restrictions on domestic activities, two factors, namely the global and China economic slowdown, contributed to a double slowdown. The recession at that time was predicted to be the worst since the Great Depression (the worldwide economic downturn in 1929–1939) [1].

Indonesia is not immune to the economic slowdown during the pandemic. Based on research, the impact of the COVID-19 pandemic affects the economy of Indonesia. It affects many sectors, such

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as transportation, tourism, trade, and health. However, among those affected sector, the household sector is the most-affected sector during the COVID-19 [2]. The severe problems caused by pandemics include a decline in GDP, an increase in unemployment, and a widening gap between rich and poor. GDP (based on expenditure) decreased by 2.45% in 2020 YoY (year over year). The open unemployment rate increased significantly in 2020 by 43.12%. Moreover, Indonesia also experienced an increase in the poverty gap index (P1) by 10.16% YoY.

Indonesia is divided into several administrative regions called provinces. Each province has several indicators of economic growth. There are several macroeconomics indicators including GDP, unemployment rates, interest rates, and Consumer Price Index (CPI) [3], [4]. Macroeconomics itself is the branch of economics that studies the behavior and performance of economy as a whole. Macroeconomics aims to understand how economy operates, what causes economic growth or recession, and how government policies (like fiscal and monetary policy) can influence the economy's overall health. In this study, the economic indicators were Gross Regional Domestic Income (GRDP), economic growth rate, and open unemployment rate. The economic growth rate is a measure of how the GDP of an economy changes over time, usually expressed in percentages.

There are two types of GRDP available at the Central Statistics Agency (Badan Pusat Statistik, BPS), namely GRDP at current prices and GRDP at constant prices. GRDP at current prices illustrates the added value of goods and services calculated using prices in the current year. GRDP at constant prices shows the added value of these goods and services calculated using prices prevailing in a particular year as the base year.

The unemployment rate is an effective indicator to observe the impact of the pandemic because the weakening of economic activity has caused mass layoffs throughout 2019 to 2020 [5], [6]. Several studies also predicted that the unemployment rate would increase during 2020 [7]. A national measurement of unemployment is open unemployment rate indicates the percentage of the labor force included in the unemployed [8].

Popular clustering algorithms for nonhierarchical approaches are k-means or k-medoids. Both algorithms have a similar work procedure that utilizes a distance matrix to determine clusters. Instead of using the average distance as in k-means, the center of the k-medoids cluster is one of the cluster members (called medoids) [9]. Other popular algorithm employs fuzzy such as c-means and subtractive clustering [10], [11]. Although k-means clustering is highly efficient in terms of processing time, it is unfortunately known to be sensitive to outliers. Hence, representative objects known as medoids—rather than centroids—are taken into consideration in k-medoids clustering, which is occasionally employed. Compared to k-means clustering, it is less susceptible to outliers because it is based on the object placed in the center of a cluster [12]. The most effective and well-liked approach for k-medoids clustering is the Partitioning Around Medoids (PAM) algorithm, which was first introduced by Kaufman and Rousseeuw in 1990. Additionally, the PAM technique was integrated into a R package and suggested for time series clustering containing the dynamic time warping also [13].

Given the time series data of economic indicators, it is more difficult to cluster time-series (or sequential) data than nonsequential data because the sequence of time series items must be considered when comparing data samples [14]. The distance that measures the distance of two time series object is Dynamic Time Warping (DTW). It is discovered that DTW distance is more resistant to time-series data clustering than other traditional measurements like the Euclidian distance.

This research is arranged as follows: an introduction, method, results and discussion, and conclusion. The research methodology contains data, data sources, and analytical methods used in this research. Research and discussion consist of descriptive analysis and clustering analysis. Finally, the conclusion is the deduction of the clustering process and recommendations for further research.

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2. Method

2.1. Materials

The data used in this study was the GRDP and the economic growth rate of each province in Indonesia. There are two types of GRDP available on the website of the BPS (www.bps.go.id): GRDP based on current prices and GRDP based on constant prices according to expenditure. In addition, the economic growth data was obtained from the Ministry of National Development Planning of the Republic of Indonesia (https://simreg.bappenas.go.id/).

2.2. Methods

After collecting data, the data was processed using R software with the help of the *dtw* package. Descriptive analysis provided information on the distribution of each data column and outliers by utilizing boxplots. Line charts were used to see data movement patterns over time.

The data was arranged by table, in which rows are the province and columns are the time series data of a variable. Clustering analysis with k-medoids and DTW was initiated by determining the optimal k value by considering the Within Sum of Squares (WSS) value. The clustering process using the number of k-optimal was validated with several measurements, namely silhouette (max), Davies-Bouldin (min), and Calinski-Haarabz (max). The results of clustering were subsequently visualized on the map. Fig. 1 displays the research flowchart.

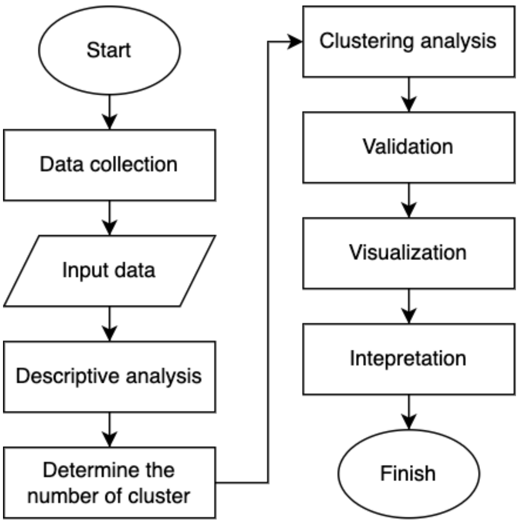

Fig. 1 Research flowchart.

2.3. Dynamic Time Warping (DTW)

The DTW distance refers to the length of the optimal alignment (i.e., the warping path) between two given time series. A greater DTW distance suggests a more pronounced difference between the two time series [15], [16]. Given two time series b_p and b_Q, where $P = p_1, p_2, \dots, p_m$ and $Q = q_1, q_2, \dots q_n$ ($m = n$ is the length of the time series). When determining the DTW distance for P and Q, the first step was to establish a distance matrix D of $m \times n$ elements. The value of individual elements (di) in this matrix can be calculated as follows [15]:

$$d_{ij} = \sqrt{\left(p_i - q_j\right)^2} \tag{1}$$

where d_{ij} denote the distance, p_i is the value of ith of P, and q_j is the value of j-th of Q. It makes it possible to generate the alignment between P and Q by locating a warping path (W). A warping path is a sequence of adjacent elements in the distance matrix that connects the lower-left ($i.e., d_{ii}$) and upper-right (d_{mn}) corners of the matrix while achieving the lowest cumulative d_{ij} values possible.

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Mathematically, a warping path is defined as $w_1, w_2, \ldots, w_k$ where $\max(m,n) \leq k \leq m+n-1$ and $w_k = (i^{th}, j^{th})$ and the length of this path is known as the DTW distance.

Among the warping paths that satisfy the above conditions, we were concerned with the optimal path that minimizes the warping cost:

$$DTW(P,Q) = \min \sum_{k=1}^{c} w_k \quad (2)$$

The following recurrence, defining the cumulative distance γ_{ij} as the distance d_{ij} found in the current cell and the minimum of the cumulative distances of the adjacent components, can be evaluated using dynamic programming to find this path [14], [17]:

$$\gamma_{ij} = d(p_i, q_j) + \min\{\gamma(i-1,i), \gamma(i,j-1), \gamma(i-1,j-1)\} \quad (3)$$

2.4. K-Medoids Clustering

The k-medoids algorithm is used to detect medoids in a cluster at its central point. K-medoids are more reliable than k-means because they use k as a representative object to reduce the total differences between data objects, whereas k-means use the sum of squared Euclidean distances. This distance metric also lowers noise and outliers [18]. The following are the algorithms of k-medoids [9], [12], [17], [19].

a. Input: k is the number of clusters, D is the data set containing n objects.
b. Output: a set of k clusters.
c. Arbitrarily choose k objects in D as the initial medoids.
d. Repeat
   - assign each remaining object to the cluster with the nearest medoid;
   - randomly select a non-medoid object, o_{random};
   - compute the new cost of the clustering when swapping the medoid o_j with o_{random};
   - if the new cost is less than the previous cost after the swapping, swap o_j with o_{random} to form a new set of k-medoids until there is no change.
e. Until no change.

2.5. Clustering Validation

This research used silhouette, Davies–Bouldin index, and Calinski-Haarabz index to validate the clustering results. The average of silhouette approach measured the quality of clustering. For data point $i \in C_I$ (data point i in cluster C_I) let:

$a(i) = \frac{1}{|C_I|-1} \sum_{j \in C_I, i \neq j} d(i,j)$ and $b(i) = \min_{J \neq I} \frac{1}{|C_J|} \sum_{j \in C_J} d(i,j)$, where $|C_I|$ is the number of points belonging to cluster C_I and $d(i,j)$ is the distance between points i and i in cluster C_I. The $b(i)$ defines the mean of dissimilarity of point i to all points in cluster C_j $(C_I \neq C_J)$. The silhouette formula defines as follows [19] [20]:

$$s(i) = \begin{cases} 1 - a(i)/b(i) & if\ a(i) < b(i) \\ 0 & if\ a(i) = b(i) \\ \frac{b(i)}{a(i)} - 1 & if\ a(i) > b(i) \end{cases} \quad (4)$$

where $a(i)$ is average dissimilarity between i and the other object within a cluster. A large $b(i)$ implies that i is very matched to its neighboring cluster. Hence, if $s(i)$ is close to 1, the data has been clustered appropriately. By applying the same reasoning, we can determine that i would be more appropriate if it were clustered in its neighboring cluster if $s(i)$ is close to -1. The datum was on the boundary of two natural clusters if the $s(i)$ value was close to zero.

The Davies–Bouldin index is the ratio of within-cluster distances to between-cluster distances. Therefore, clusters that are farther apart and less dispersed will result in a better score. Cohesion is the sum of the data's proximity to the cluster center point of the cluster it belonged to, while separation is based on the distance between the cluster center points to the cluster [21].

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$$DB = \frac{1}{k}\sum_{i=1}^{k}\max_{i\neq j} R_{ij} \tag{5}$$

where $R_{ij} = \frac{s(i)+s(j)}{d(i,j)}$ is the similarity measurement, $s(i)$ is the average distance of each point i to its cluster's centroid (cluster diameter).

The Calinski-Harabasz index is an evaluation index based on the ratio of between cluster and within clusters and is defined as follows [22].

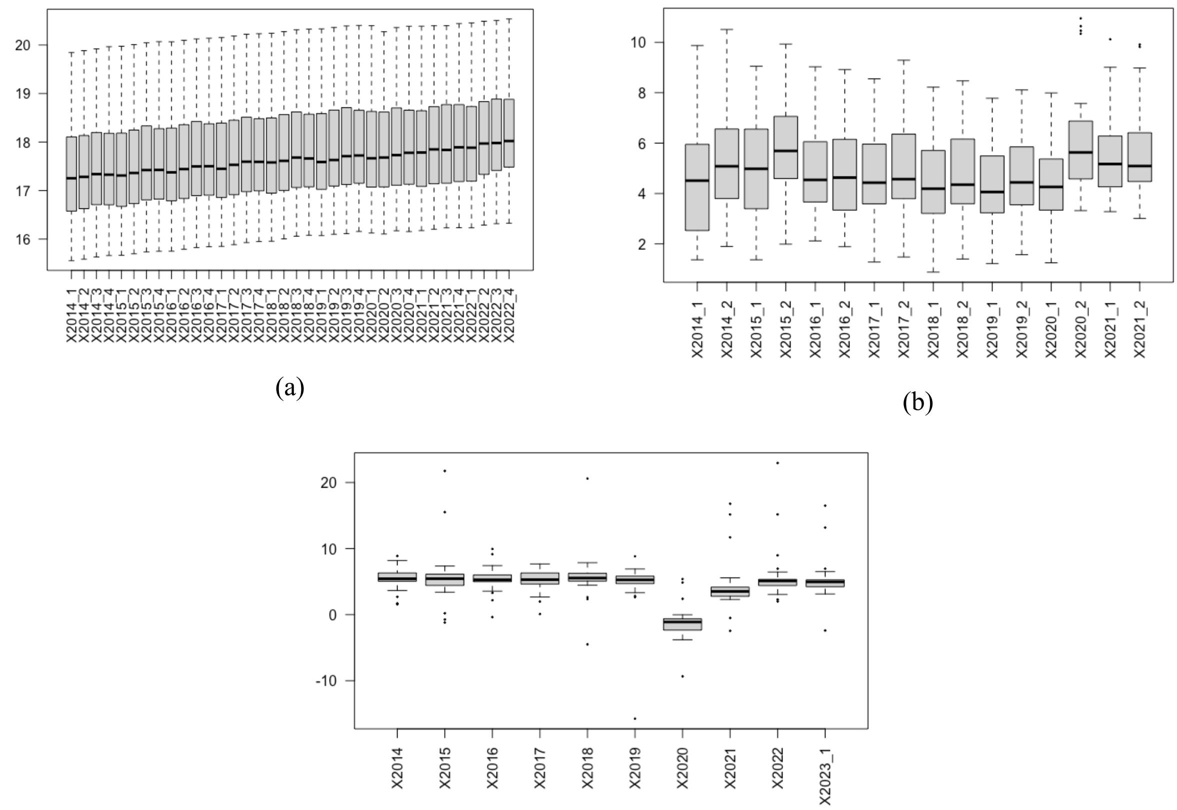
$$CH(K) = \frac{B(K)(N-K)}{W(K)(K-1)},\ B(K) = \left(\sum_{k=1}^{K} a_k \left|\left|\bar{x}_k - \bar{x}\right|\right|^2\right), \quad W(K) = \left(\sum_{k=1}^{K}\sum_{C(J)=k}\left|\left|x_j - \bar{x}_k\right|\right|^2\right) \tag{6}$$

where k is the number of clusters, $B(K)$ is the inter-cluster divergence (betweenness), and $W(K)$ is intra-cluster divergence (within). The higher the ratio is, the better the clustering.

3. Results and Discussion

3.1. Descriptive Analysis

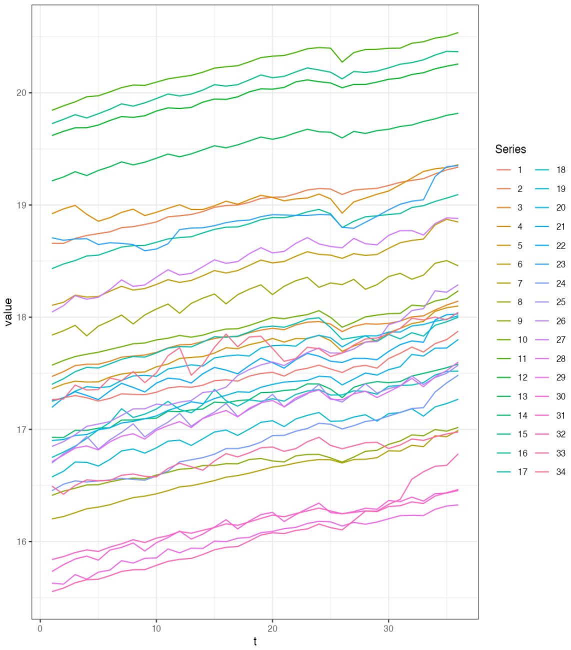
Fig. 2 shows box plots of economic indicators. The GRDP had symmetric box plots for almost all the years. There are outliers in the unemployment rate and economic growth. Moreover, North Kalimantan province's open unemployment rate had two missing values in 2014. We imputed the missing values using a moving average with an order of two.



(a) (b) (c)

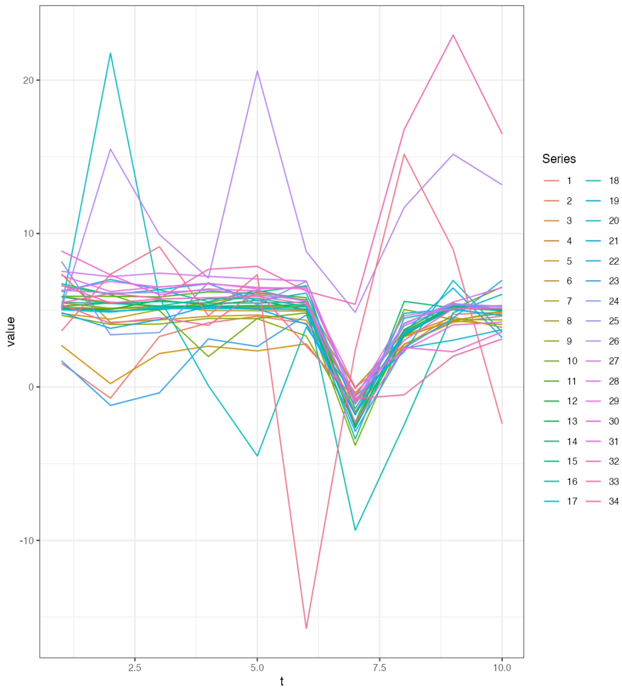
Fig. 2 Boxplot of (a) GRDP, (b) open unemployment rate, (c) economic growth.

Fig. 3 displays line charts of economic indicators, including (a) GRDP, (b) open unemployment rate, and (c) economic growth. Almost every province in Indonesia had a GRDP trend pattern that tended to increase. The open unemployment rate for each province also had something in common, namely, it increased sharply at the start of the pandemic and gradually decreased in 2021. In addition, almost all provinces had negative economic growth rates in 2020.



(a)

(b)



(c)

Fig. 3 Line chart for all province of (a) GRDP, (b) open unemployment rate, and (c) economic growth.

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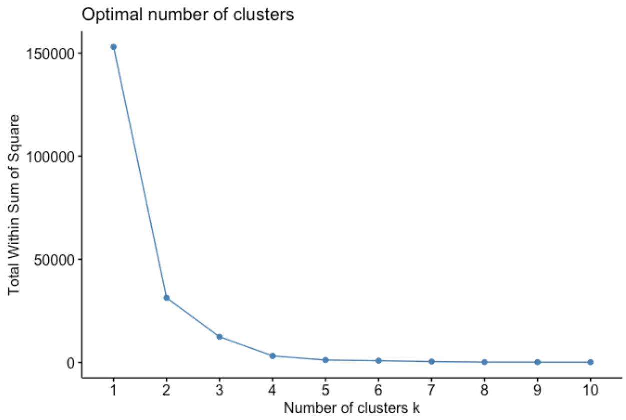
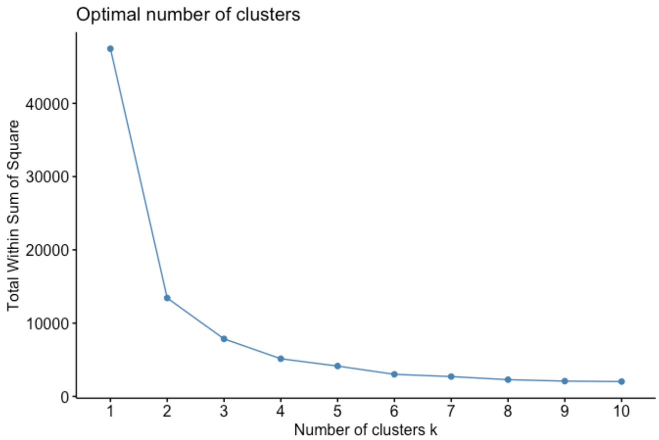
3.2. Clustering Analysis

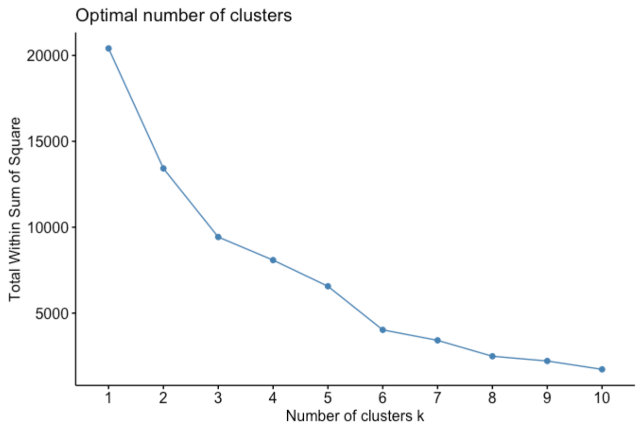
This study employed the elbow method to take the initial number of clusters (k) by calculating the WSS value. We chose the k where the WSS value remained constant or almost the same. Based on the WSS in Fig. 4, we proceeded with k=3 and k=4 for each economic indicator.



(a)



(b)



(c)

Fig. 4 WSS for (a) GRDP, (b) unemployment, (c) economic growth.

After clustering using the initial number of clusters, we calculated the index to validate the cluster results. Silhouette index ranged from [-1,1]: a high value indicates that the object is well matched to its cluster and poorly matched to neighboring clusters. The Davies-Bouldin index defines a ratio between the cluster scatter and the cluster's separation; a lower value indicates better clustering. The Calinski-Harabasz index, also known as the variance ratio criterion, is the ratio of the sum of between-cluster dispersion and inter-cluster dispersion for all clusters, the higher the score, the better the performance.

Table 1. Validation Score

	GRDP		**Open Unemployment Rate**		**Economic Growth Rate**	
	k = 3	*k = 4*	*K =3*	*k = 4*	*k = 3*	*k = 4*
Silhouette (max)	0.66	0.45	0.49	0.30	0.16	0.11
Davies-Bouldin (min)	0.21	0.65	0.74	0.86	2.84	3.06
Calinski-Haarabz (max)	39.55	27.07	29.77	22.04	3.56	4.47

Based on the validation results in Table 1, k = 3 was considered more optimal for clustering the three indicators. The validation values for the open unemployment rate and economic growth were not very good (for both k). The silhouette value was closer to 0, suggesting that the clusters were almost indifferent. Davies-Bouldin scored relatively high, while Calinski-Haarabz was low. Based on Figure 3, each province's economic indicators pattern was virtually identical. The difference lay in the number of indicators. In addition, the movement of economic indicators for all provinces from year to year had a similar pattern.

Table 2, Table 3, Table 4 are the results of clustering including the number of members in each cluster (cluster size), the average distance of each pair of members within a cluster, and the cluster center (medoids). The number at the center of the cluster is the order of the province in the data.

Table 2. Clustering Results of GRDP

	Cluster 1	**Cluster 2**	**Cluster 3**
Cluster size	7	23	4
Average distance	0.21	0.65	0.73
Center of cluster	16th	28th	12th

For GRDP, the number of provinces in cluster 1, cluster 2, cluster 3 was 7 provinces, 23 provinces, and 4 provinces, respectively. The center of cluster 1 was Banten, the center of cluster 2 was Sulawesi Tenggara, and the center of cluster 3 was Jawa Barat. Cluster 3 comprised only four provinces: Jawa Barat, DKI Jakarta, Jawa Tengah, and Jawa Timur. Cluster 2 consisted of provinces in Sumatra, Kalimantan, Sulawesi, Nusa Tenggara, and Papua.

Table 3. Clustering Result of Open Unemployment Rate

	Cluster 1	**Cluster 2**	**Cluster 3**
Cluster size	4	11	20
Average distance	13.42	12.42	13.40
Center of cluster	12th	2nd	5th

Based on Table 3, Jawa Barat was the center for cluster 1 with others member such Kepulauan Riau, Banten, and DKI Jakarta. Sumatera Utara was the center of cluster 2 and Jambi was the center of cluster 3.

Table 4. Clustering Results of Economic Growth

	Cluster 1	**Cluster 2**	**Cluster 3**
Cluster size	11	20	3
Average distance	18.78	13.75	15.89
Center of cluster	25th	8th	21st

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Based on Table 4, Sulawesi Utara was the center of cluster 1 and Lampung was the center of cluster 2. Kalimantan Tengah was the center of cluster 3 with other members such Nusa Tenggara Barat and Sulawesi Barat.

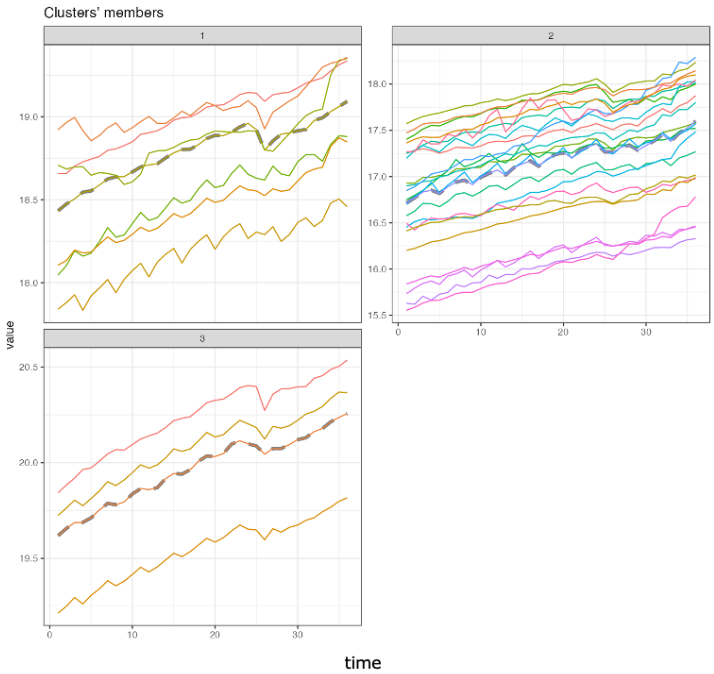

Fig. 5 Clustering result for GRDP.

Based on the Fig. 5, clusters 1, 2, and 3 had a similar trend of GRDP in which there was a tendency to increase from year to year. The pandemic certainly caused quite a significant decline. However, this decline was not lower than the GRDP value at the beginning of the data, 2014. Cluster 3 had the highest GRDP value compared to the other two clusters. Cluster 2 had a moderate GRDP value, while cluster 1 was the lowest.

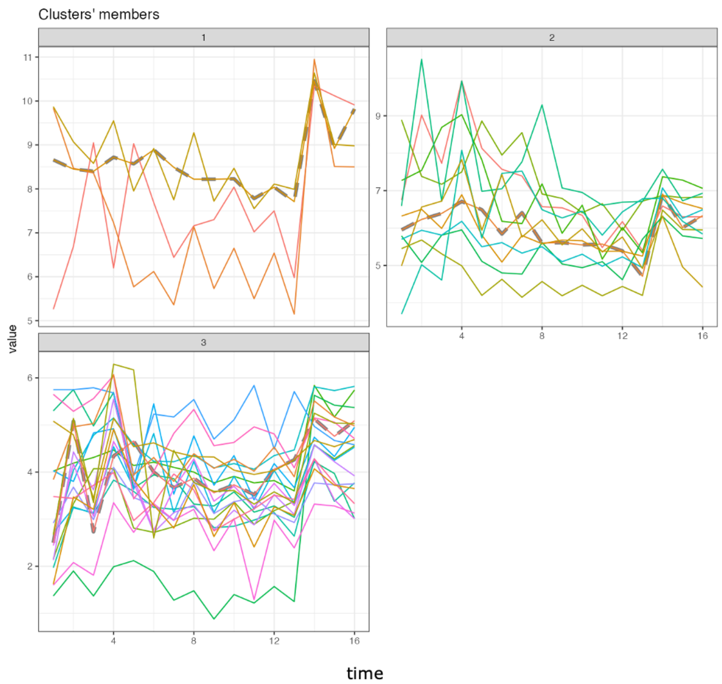

Fig. 6 Clustering result for the open unemployment rate.

Fig. 6 shows the clustering result for unemployment. Cluster 1 had a significant unemployment rate pattern at the beginning of the pandemic. Cluster 2 had an unemployment pattern that tended to decrease from year to year before the pandemic but increased due to the pandemic. Even so, the unemployment rate during the pandemic in several provinces was not higher than that at the beginning of the data period (2014 and 2015). Cluster 3 had a similar pattern to cluster 1. However, the unemployment rate in this cluster was lower than that in cluster 1 on average.

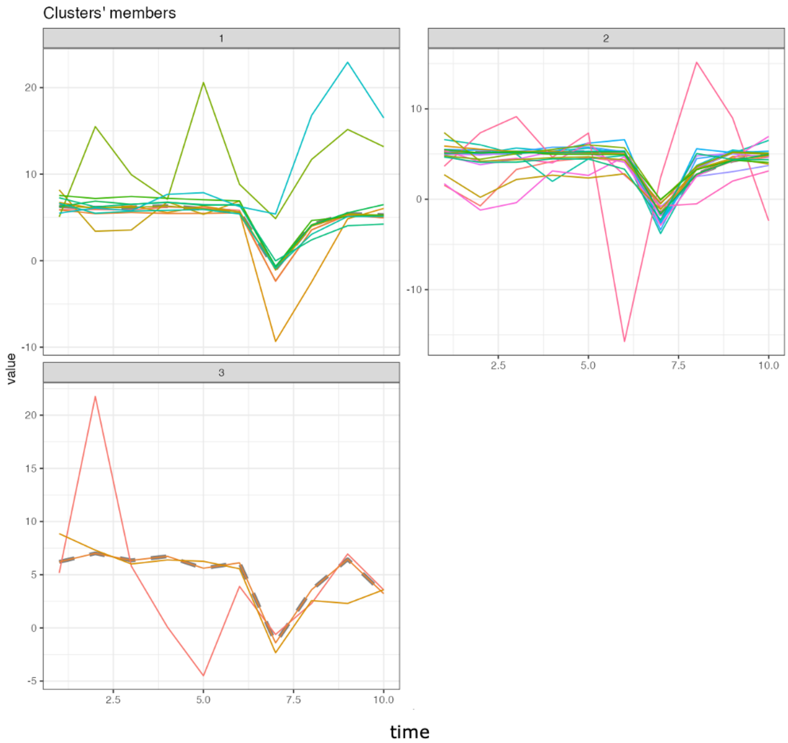

Fig. 7 Clustering result for the economic growth.

Based on the Fig. 7, cluster 2 had the sharpest decline in economic growth compared to other clusters. The severity of the decline was followed by cluster 1, then cluster 3. Many members in clusters 1 and 2 had economic growth ranging between 5–10% from 2014 to 2019, then started to fall in 2020. The situation gradually improved in early 2021 until the first trimester of 2023. In cluster 3, economic growth weakened again at the beginning of 2023, which did not happen in the other two clusters. In cluster 1, two provinces had different movements than other cluster members. While in cluster 2, there was one different province. The movement of economic growth for these provinces was erratic from the beginning.

Prior to 2019, economic conditions (indicators) were quite stable. In Indonesia, economic growth was affected by human capital. According to the research result, however, labor and technology were the main drivers of economic growth, whereas human capital was successful in driving the economy over the long term. Technology and human capital had a substantial long-term impact on Indonesia's economic growth from 1984 to 2019 [23].

Visualization using maps helps identify economic indicators more easily [24]. The red indicates clusters with conditions that need to be supervised because they experience a sharp decline or have low indicator values. Yellow is an intermediate condition, while green is a good or quite good condition. Good conditions mean that the value of economic indicators fell during the pandemic, then gradually improved at the end of 2022.

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Fig. 8 Map of GRDP cluster.

Based on Fig. 8, every province on the island of Java has a high GRDP, except Yogyakarta. Almost every province on the islands of Sumatra, Kalimantan, Sulawesi, the Maluku Islands, Bali, Nusa Tenggara, and Papua had a moderate GRDP.

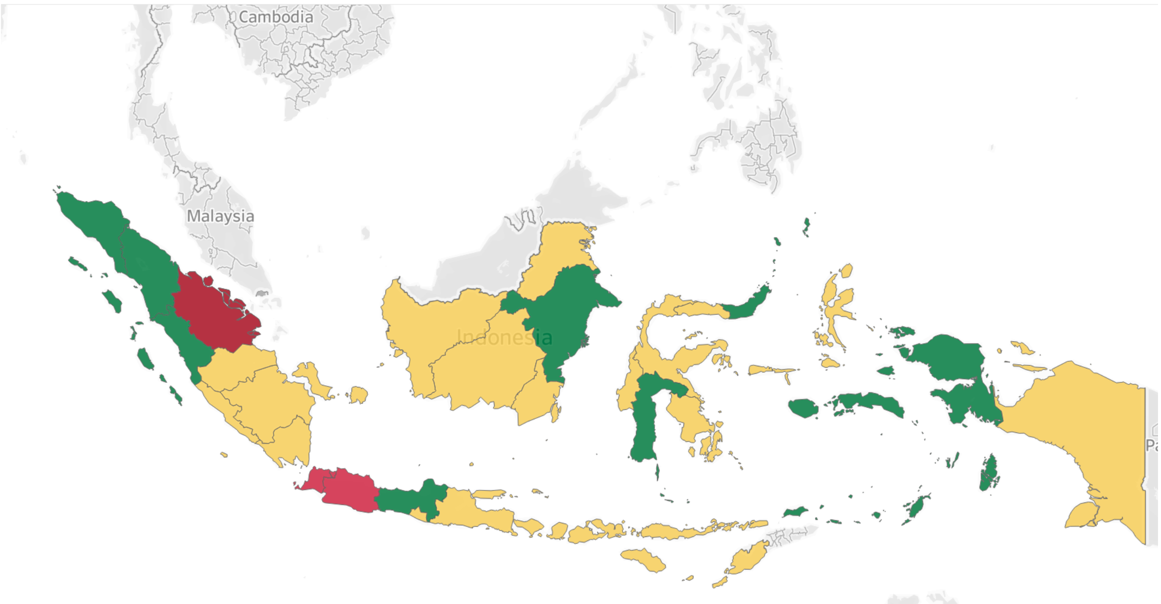

Fig. 9 Map of the open unemployment rate.

Based on Fig. 9, the open unemployment rate needed to be overlooked in the provinces of DKI Jakarta, Jawa Barat, Banten, and Riau. Meanwhile, all Sumatra, Papua, and East Nusa Tenggara provinces were in low condition for economic growth, and so were several provinces on the islands of Java and Kalimantan. Bali, Nusa Tenggara Barat, Kalimantan Tengah, and Sulawesi Barat had good economic growth.

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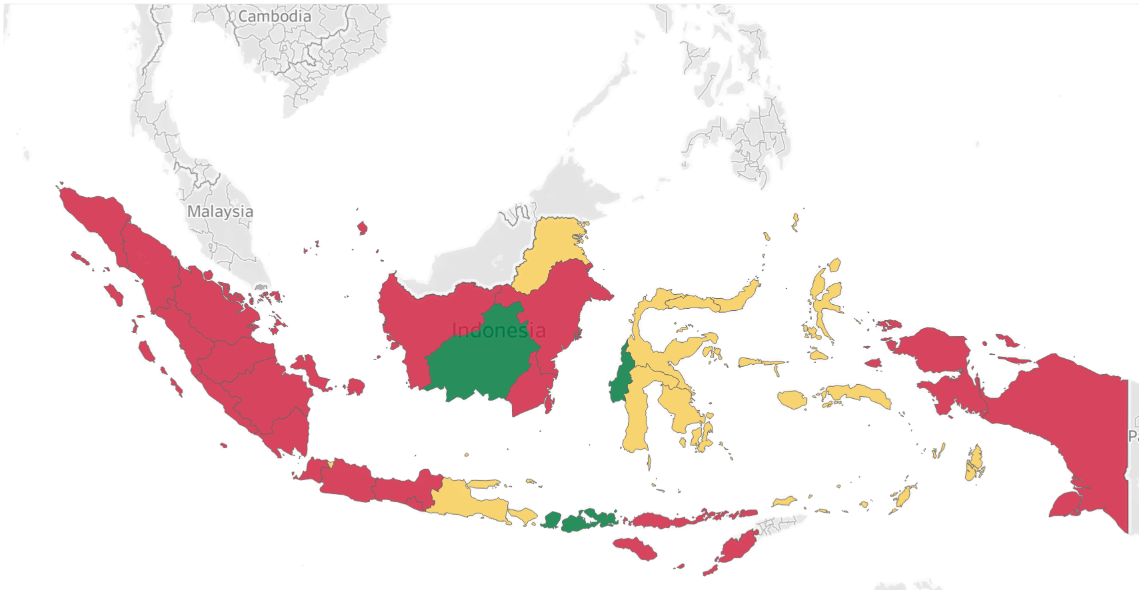

Fig. 10 Map of the economic growth

Based on Fig. 10, most of provinces in Indonesia had a bad economic growth. Only three provinces (Kalimantan Tengah, Nusa Tenggara Barat, and Sulawesi Barat) had a good economic growth. They only had negative growth in 2020, while others might have negative growth in 2019 and 2021.

4. Conclusion

The pattern of economic indicators in each province in Indonesia was not very diverse and even tended to be indifferent. This problem caused difficulties in clustering. It was proven by the index validation value that was not good for the three indicators. In general, the difference between clusters is only the level of increase or decrease in economic indicators.

Despite the pandemic, GRDP continued to increase out of the three indicators. The economic growth rate collectively fell to a negative value in 2020. Meanwhile, the open unemployment rate increased significantly in 2020. However, the condition has been getting better since the end of 2020 until now.

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