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The impact of the COVID-19 pandemic on O-D flow and airport networks in the origin country and in Northeast Asia

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ABSTRACT

The ongoing COVID-19 pandemic has posed a global threat to human health. In order to prevent the spread of this virus, many countries have imposed travel restrictions. This difficult situation has dramatically affected the airline industry by reducing the passenger volume, number of flights, airline flow patterns, and even has changed the entire airport network, especially in Northeast Asia (because it includes the original disease seed). However, although most scholars have used conventional statistical analysis to describe the changes in passenger volume before and during the COVID-19 outbreak, very few of them have applied statistical assessment or time series analysis, and have not even examined how the impact may be different from place to place. Therefore, the purpose of this study was to identify the impact of COVID-19 on the airline industry and affected areas (including the origin-destination flow and the airport network). First, a Clustering Large Applications (CLARA) algorithm was used to group numerous origin-destination (O-D) flow patterns based on their characteristics and to determine if these characteristics have changed the severity of the impact of each cluster during the COVID-19 outbreak. Second, two statistical tests (the paired *t*-test and the Wilcoxon signed-rank test) were utilized to determine if the entire airport network and the top 30 hub airports changed during COVID-19. Four centrality measurement indices (degree, closeness, eigenvector, and betweenness centrality) of the airports were used to assess the entire network and ranking of individual hub airports. The study data, provided by The Official Aviation Guide (OAG) from December 2019 to April 2020, indicated that during the COVID-19 outbreak, there was a decrease in passenger volume (60%–98.4%) as well as the number of flights (1.5%–82.6%). However, there were no such significant changes regarding the popularity ranking of most airports during the outbreak. Before this occurred (December 2019), most hub airports were in China (April 2020), and this trend remain similar during the COVID-19 outbreak. However, the values of the centrality measurement decreased significantly for most hub airports due to travel restrictions issued by the government.

1. Introduction

Airlines provide long-distance transportation between continents and have been a popular mode of transportation for decades. More than any other mode of transportation (ocean or ground), air transport has benefited from advanced technological innovations, which have had a revolutionary effect on long-distance travel. However, with these advancements have come to some challenges. For example, the risk of global pandemic transmission has increased in recent years (Brockmann and Helbing, 2013) in part due to the airline industry with regard to diseases such as MERS in 2012 (Zaki et al., 2012) and Ebola in 2014.

(Bogoch et al., 2015). In response authorities must enforce lockdown or travel restrictions to block the disease-spreading pathways; however, the impact and social cost of these policies must be evaluated.

Compared to previous pandemic outbreaks, COVID-19 has had a more devastating impact around the world. In the first few months of 2020, the disease spread rapidly to almost every country and led to extraordinary and previously inconceivable travel bans and lockdowns (Maneeop and Kotcharin, 2020; Monmousseau et al., 2020; Sun et al., 2020; Suzumura et al., 2020). The reactions of countries to the emergence of COVID-19 were quite diverse. When the World Health Organization (WHO) declared the COVID-19 outbreak a global pandemic in

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Mach 2020), most countries were placed under partial or even full mobility/flight restrictions, which limited international travel considerably (Monmousseau et al., 2020). Although travel restrictions and flight cancellations slowed down the spread of COVID, they severely disrupted various aspects of the transportation system (Maneenop and Kotcharin, 2020; Monmousseau et al., 2020; Sun et al., 2020; Suzumura et al., 2020).

COVID-19 has impacted air transportation in several important ways, such as reducing passenger volume (Iacus et al., 2020), the number of flights (Nizetić, 2020; Suzumura et al., 2020), and airport network connectivity (Sun et al., 2020). Due to the fact that many researchers (Iacus et al., 2020; Nizetić, 2020) only used graphs and descriptive statistics to roughly evaluate the potential reduction of flights during COVID-19, this study utilized the spatial analysis of the Origin-Destination (O-D) flow to get more detailed results. The O-D flow here is determined as the number of direct flights that are traveling between origin and destination airports within a specific time interval (Tennekes and Chen, 2021). Only a few studies (Sun et al., 2020; Suzumura et al., 2020) have been able to illustrate the airline flow changes and detect airport network trends because, in part, they didn't check the airport popularity/ranking changes specifically. Therefore, the purpose of this study was to explore the impact of COVID-19 on passenger volume, the number of flights, and airport network connectivity.

In this study, two different approaches were used to identify the differences in airline O-D flow characteristics before and during the COVID-19 outbreak. Due to the fact that it is very difficult to identify changes in airline flow with illustrations using the entire dataset, a Clustering Large Application (CLARA) was implemented to group all airline O-D flow into several clusters based on their characteristics in both study periods. Our hypothesis states that some variables affect COVID-19's impact on O-D flow, such as distance, domestic/international flights, or if the origin or destination point is connected to China or not. The impact before and during the pandemic were evaluated based on passenger volume and the number of flights. In addition, four centrality measurements were used to analyze the pandemic changes in networks, such as degree centrality, closeness centrality, eigenvector centrality, and betweenness centrality. These indices can illustrate the importance of an airport. Then, a paired *t*-test and Wilcoxon signed-rank test were used to determine the significance of the changes in the O-D flow and airport network before during, and during the pandemic.

This paper is organized as follows. Section 2 is a literature review on related topics and methodologies. Section 3 describes the data and research methodology utilized in our study. Section 4 provides an analysis of the results, and the conclusion is contained in Section 5.

2. Literature review

2.1. Impact of infectious diseases on air transportation

Past pandemics such as SARS in 2002 and H1N1 in 2009 have caused serious airline traffic disruption. Researchers discovered a strong association between pandemic outbreaks and recessions in the airline industry due to decreases in the number of passengers (Chou et al., 2004; Iacus et al., 2020; Lee and Warner, 2006; Pine and McKercher, 2004), the number of flights (Bajardi et al., 2011; Nizetić, 2020; Suzumura et al., 2020) and disruption of airport network connectivity (Sun et al., 2020). For example, Severe Acute Respiratory Syndrome (SARS) in 2002 reduced passenger volume by approximately 80% in Hong Kong (Pine and McKercher, 2004). In Taiwan, it decreased by approximately 59.2% (Chou et al., 2004). On a larger scale, SARS decreased the passenger volume up to 70% on the Asian continent (Lee and Warner, 2006). The H1N1 virus, known as swine flu, also affected the airline industry significantly by decreasing approximately 40% of flights in 2009 (Bajardi et al., 2011).

Previous scholars found that aviation plays an important role in the

spread of diseases, such as SARS/MERS (Poletto et al., 2016; Wong et al., 2015), H1N1 (Bajardi et al., 2011), and others, transforming a (local) epidemic into a (global) crisis (Dawood et al., 2012). More recently, COVID-19 has become a new global pandemic, causing more than three million deaths worldwide (May 5th, 2021) (Worldometers.info, 2021). Compared to SARS and H1N1, COVID-19 has had a more devastating impact on human health, resulting in the highest number of casualties. According to a new study by Sun et al. (2021a), Abate et al. (2020), and Bauer et al. (2020), the pandemic has had a particularly devastating impact on the aviation industry. Near the end of February, there were approximately 8,000 international flights per day. However, by the end of March after the COVID-19 outbreak, the number of daily flights dropped dramatically to less than 1,000 (roughly 10% of the regular seasons) (Suzumura et al., 2020). In addition, COVID-19 reduced passenger volume in Europe by approximately 89% from January to April 2020 (Nizetić, 2020). In the United States, the number of flights decreased by nearly 30% (Suzumura et al., 2020). With regard to network connectivity, airport traffic in international hubs in Turkey, Russia, and France (Sun et al., 2020) was greatly reduced due to the increasing numbers of confirmed Covid-19 cases (Tanrıverdi et al., 2020). Thus, an infectious disease directly impacted passenger volume, number of flights, and airport network connectivity, particularly because of lockdown policies that reduced people's mobility and their risk of becoming infected (Kim and Kwan, 2021; Zhang et al., 2020). Thus, the purpose of this study was to utilize the O-D flow data to examine how COVID-19 affects the passenger volume, number of flights, airline flow patterns, and airport rankings.

2.2. Clustering algorithm

Several scholars have used various approaches to analyze the impact of COVID-19 on air travel. For example, Iacus et al. (2020) and Nizetić (2020) used statistical analysis to explore changes in passenger volume and number of flights pre-and during-outbreak. Not surprisingly, these factors declined sharply during the pandemic outbreak. However, these traditional methods cannot show if this impact varied from place to place, such as whether or not there was an increase at the airports nearer to the country of origin (Fang et al., 2020). Therefore, we utilized origin-destination (O-D) flow data from airlines to determine how COVID-19 affected this flow, which is shown on the following maps. It must be noted that most researchers focused on the change in the absolute value of demand instead of the relative change (such as the ranking or popularity of various airports) before and during the spread of COVID-19. Thus, in this study, we identify two critical gaps that must be addressed: determining the COVID-19's impact on origin-destination airline flow and the changes that have occurred in airport centrality.

However, analyzing the massive O-D flow data and illustrating changes pre-and during-pandemic is a challenge. Therefore, we applied a clustering method to group raw O-D flow data to reveal flow mobility trends and spatial patterns based on their similarities and characteristic (Guo et al., 2020). Four key factors were used for clustering, including flight distance (long, medium, short), flight type (international/domestic), whether or not the airport of origin, and the destination airport were connected to China. Since this information is binary or categorical, supervised learning is unsuitable because it is heavily reliant on labeled data to calculate all forms in the training phase, thus it could produce decent classification results (Fang et al., 2021). Therefore, an unsupervised learning method, such as clustering, is more suitable for this kind of dataset.

Currently, various clustering algorithms have been developed and optimized, the most popular of which is the k-means-based clustering algorithm that is usually used to group O-D flow data and its attributes (Anderlucci and Hennig, 2014) in order to analyze the categorical and binary data. These include the Partitioning Around Medoid (PAM), the Clustering Large Application (CLARA) (Anderlucci and Hennig, 2014; Azimi and Zhang, 2010; Popovich et al., 2021), Latent Class Clustering

(LCC) (Sivasankaran and Balasubramanian, 2020) and the Clustering Large Applications based on Randomized Search (CLARANS) (Schubert and Rousseeuw, 2019). The first two have been commonly implemented in transportation studies (Popovich et al., 2021) and are suitable for exploring both binary and categorical data (Watve et al., 2014). PAM, also known as k-medoids, is an algorithm for clustering correlated elements through medoids, which are a representation of cluster centers derived from the minimum sum dissimilarity matrix. CLARA is an algorithm for clustering the correlated elements by sampling multiple times, and PAM is utilized to select the best medoid. CLARA performs better when a large dataset is involved, while PAM is more time-consuming and less efficient (Anderlucci and Hennig, 2014). When PAM and CLARA were compared to the LCC algorithm, they yielded higher average silhouette widths than LCC. These findings suggest that PAM and CLARA successfully produce better separation and compactness of clusters. In addition, Nayyar and Puri (2017) found that CLARA performed better with thousands of samples compared to PAM. In addition, when Azimi and Zhang (2010) applied fuzzy c-means and CLARA to classify freeway traffic flow conditions, they determined that the CLARA algorithm produced more consistent results than the fuzzy-c means technique.

Another advanced clustering method, Clustering Large Applications based on Randomized Search (CLARANS), which combines the concept of PAM and CLARA was also employed to group the data (Watve et al., 2014). CLARANS dynamically draws from a random sample of neighbors in each step, while the CLARA technique is confined to the given sample. CLARANS produced higher cluster purity than the hierarchical-based algorithms, such as ROCK. Compared to CLARA, CLARANS appears to be comparable based on the number of loss total deviation, when the number of clusters is below 70 (Schubert and Rousseeuw, 2019). However, according to Schubert and Rousseeuw, CLARANS was less efficient than CLARA with regard to processing time. CLARANS tends to have a longer processing time because it assigns random medoids to the dataset and checks it one by one until the optimal cluster is formed. In sum, CLARA is faster than CLARANS because it creates subsamples and assigns medoids within the subsample. However, their performance is similar if the number of clusters is small.

Based on the literature review, we chose the CLARA algorithm because it is more effective than PAM for clustering thousands of samples (Nayyar and Puri, 2017). Furthermore, this method was chosen because airline O-D flow is made up of both categorical and binary data, and CLARA provides better cluster separation and compactness for clustering discrete data by producing higher than average silhouettes than LCC and PAM (Anderlucci and Hennig, 2014). In addition, not only does it provide faster computational running time but when the number of clusters (k) is small, the quality of CLARA remains comparable to CLARANS (Schubert and Rousseeuw, 2019).

2.3. Centrality metrics

For quantifying the impact of COVID-19 on airport networks, network centrality measurement was also employed in this study. It is commonly used for identifying 'central' nodes of the air transport system (main/hubs/popular airports) to establish the focal airport that is most connected within the entire airline network. Several researchers have used single or two centrality measurements to analyze the evolution of the global air transport network (Cheung et al., 2020; Sun et al., 2017; Wandelt et al., 2017; Hossain and Alam et al., 2017) or to evaluate the impact of COVID-19 on this network (Sun et al., 2020, Nikolaou and Dimitriou, 2021). For example, Cheung et al. (2020) successfully used a centrality measurement to calculate the importance of an airport based on the number of its connections (degree and eigenvector centrality), and the importance of an airport as a transit point (betweenness centrality). Their results show that Sydney Airport (SYD) and Singapore Airport (SIN) were considered to be popular transit airports particularly

from 2006 to 2016, while Washington (IAD) and Frankfurt (FRA) airports were consistently utilized as hubs in North America and Europe. This method was very effective for measuring the robustness of the worldwide airport network (Sun et al., 2017) and for showing the impact of COVID-19 trends (Nikolaou and Dimitriou, 2020). Based on Sun et al.'s (2020) findings, the degree centrality dropped by approximately 50% during the pandemic, which means that, on average, each airport lost half of its destinations. However, previous researchers only focused on explaining the overall trend of the airport network without specifically highlighting changes in the popularity of individual airports and top hub airports during the COVID-19 outbreak. Thus, in order to fill this gap, four metrics, including degree centrality, closeness centrality, eigenvector centrality, and betweenness centrality were utilized in this study to measure the centrality and the corresponding impact of COVID-19 on all airports and top 30 hub airports. Then, statistical tests (a paired *t*-test and a Wilcoxon signed-rank test) were employed to reveal any significant changes in airport popularity before and during COVID-19.

3. Data and methodology

3.1. Data

This study focused on Northeast Asia, the place of origin for COVID-19, which has suffered the most impact. The airport data for this study was obtained from the OAG traffic analyzer. There were 362 airports and nine countries included in this study, such as Russia, Mongolia, Japan, North Korea, South Korea, China, Taiwan, Hongkong, and Macau. The dataset was composed of airport codes, city names, countries, and their coordinates, as well as passenger numbers and flight distances (Table 1). The passenger numbers were determined based on O-D flow in December 2019 and April 2020. In addition, the flight distances were calculated based on the great circle distance between the departure airport and the arrival airport.

In this study, the O-D flow refers to the number of direct flights traveling between an origin and destination airport per month, which is a term that is commonly used in other studies. According to recent studies by Guo et al. (2021) and Sun et al. (2020), an airport network is interpreted as nodes (airports) and links (direct flights between airports). Furthermore, the direct link between airports demonstrates the strong ties between Northeast Asian countries (Sun et al., 2021b; Zhang et al., 2022), and this network will illustrate the dynamic international connectivity during the pandemic. There were both international and domestic flights included. Pre-COVID-19 was defined as before December 2019, and the pandemic period was set as April 2020 onward. Following the outbreak, the number of airports in operation fell from 362 to 344. There were 2,370 O-D flow flights in December 2019 and only 1,685 in April 2020. Similarly, the average passenger numbers and flight distances also decreased during the COVID-19 period (Please refer to Table 2 for the descriptive statistics.).

3.2. Methodology

3.2.1. CLARA

CLARA is an enhanced version of the k-medoid (PAM) method that features reduced computational time and minimal resources when a large number of observations are involved. CLARA is utilized to analyze a subset of the data rather than the entire dataset and employs the PAM algorithm to generate the most accurate set of medoids (Wei et al., 2003). In this study, the number of subsets used is 50. This number of subsets was chosen because it produces the best separation for each cluster (based on silhouette analysis) while also requiring the least amount of computation time. In addition, the results of the CLARA algorithm were stable and reproducible especially with larger sample sizes (Garge et al., 2005).

Steps Followed for Utilizing the CLARA Algorithm:

Table 1
OAG O-D flow dataset.

| ID | Dep. Airport Code | Dep. Country Name | Lat Dep. | Long Dep. | Arr. Airport Code | Arr. Country Name | Lat Arr | Long Arr | Passenger | Flight Distance (km) |
|-------|-------------------|-------------------|----------|-----------|-------------------|-------------------|---------|----------|-----------|----------------------|
| OD_01 | FUK | Japan | 33.586 | 130.451 | HND | Japan | 35.552 | 139.780 | 104783 | 879 |
| OD_02 | SZX | China | 22.639 | 113.811 | SHA | China | 31.198 | 121.336 | 79274 | 1207 |
| OD_03 | NRT | Japan | 35.765 | 140.386 | ICN | South Korea | 37.469 | 126.451 | 13091 | 1255 |
| OD_04 | TPE | Taiwan | 25.078 | 121.233 | HKG | Hong Kong | 22.309 | 113.915 | 9881 | 805 |

Table 2
Descriptive statistics dataset.

| Before COVID-19 (December 2019) | | | | |
|---------------------------------|---------|--------|---------|-----------|
| Airports in Operation: 362 | | | | |
| Number of O-D flows: 2,370 | | | | |
| | Minimum | Median | Maximum | Average |
| Passengers | 13 | 2,725 | 350,928 | 11,084.94 |
| Flight Distances | 23 | 1,086 | 5,047 | 1,242.59 |
| During COVID-19 (April 2020) | | | | |
| Airports in Operation: 344 | | | | |
| Number of O-D flows: 1,685 | | | | |
| | Minimum | Median | Maximum | Average |
| Passengers | 12 | 983 | 196,702 | 3,969.39 |
| Flight Distances | 23 | 941 | 5,047 | 1,095.32 |

- Multiple fixed-size subsets were randomly created from the original dataset.
- The PAM algorithm was run on each subset and the k-number representative objects were selected as medoids. Each O-D flow in the entire data set was then assigned to the nearest medoid.
- The sum of the observations' dissimilarities was determined to their nearest medoid, which was used to assess the quality of the clustering.
- The sub-dataset with the smallest sum was saved. Then, further analysis was conducted on the final partition.

The mean dissimilarity between every observation in the entire dataset was used to determine the quality of the medoid, which is regarded as the cost function. A lower-cost function value corresponds to a better clustering result. The cost function formula is shown below:

$$Cost(M, D) = \frac{\sum_{i=1}^n \text{dissimilarity}(OD_i, \text{rep}(M, OD_i))}{n} \quad (2)$$

Where M is a set of selected medoids, and D is the dataset to be clustered. (OD_i, OD_j) represent the dissimilarities between O-D flow i (OD_i) and O-D flow j (OD_j) in dataset D , and $\text{rep}(M, O_i)$ is a medoid in M which is closest to OD_i .

R was employed in this study to run the CLARA algorithm. In order to utilize this algorithm in R, the "cluster" package was installed. It was

required that the data be in the form of a numeric data matrix or data frame and each row be associated with an O-D flow and each column corresponds to an O-D flow characteristic. These characteristics included flight distances, whether the flights were domestic or international, and whether or not the flights were bound for China. This algorithm generates a class object consisting of the O-D flow dataset divided by the K clusters.

Silhouette analysis was used in this study to determine the appropriate number of clusters (Thinsungnoena et al., 2015). This value was utilized to measure the degree of similarity between an object (OD-flow here) and its own cluster. When the silhouette value is 1, the object is exactly matched to its own cluster. However, if the value is -1 , this often means that the OD-flow has been assigned to an incorrect cluster. In other words, a higher silhouette value indicates that the corresponding cluster result is more accurate. According to the results of the silhouette analysis, shown in Fig. 1, the number of recommended clusters in the two periods under study differed according to the highest silhouette coefficient. Prior to the pandemic, the highest coefficient was 0.996 within twelve clusters (Fig. 1a); however, during the peak of the pandemic, it decreased to 0.999 within eleven clusters (Fig. 1b). Due to the fact that the coefficient in the twelve clusters dropped significantly during COVID-19, eleven clusters were used since the coefficient value was also comparable to the twelve clusters before the outbreak.

3.2.2. Network centrality

In order to evaluate changes in the airport network due to COVID-19, a network centrality method was used to estimate the importance of nodes (airport) via several centrality metrics including degree centrality, closeness, betweenness, and eigenvector centrality. In the following explanation as well as in Fig. 2, we briefly define and illustrate these centrality metrics.

- Degree Centrality** is a measurement of a node based on how many edges it has, which include incoming and outgoing links. In Fig. 2, point L has the highest degree of centrality because it has the most connections with other airports (Nikolaou and Dimitriou, 2021). The top 30 highest value of degree centrality is assumed as a major hub airports since it connects to many airports.

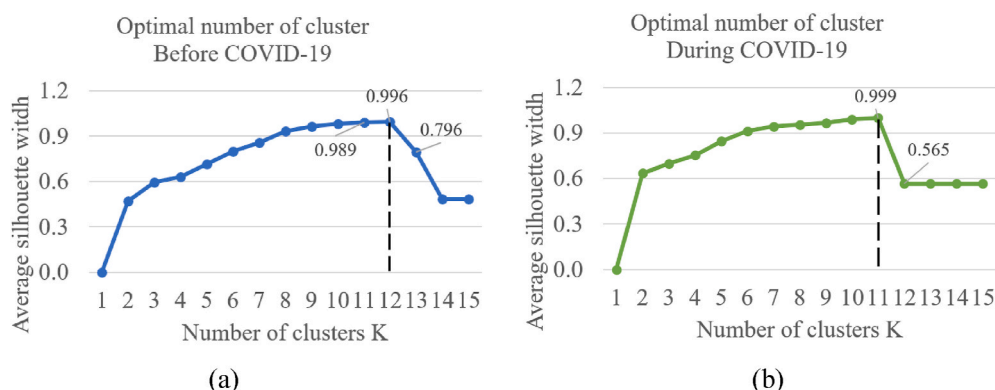


Fig. 1. The results of the silhouette analysis, (a) Before COVID-19; (b) During COVID-19.

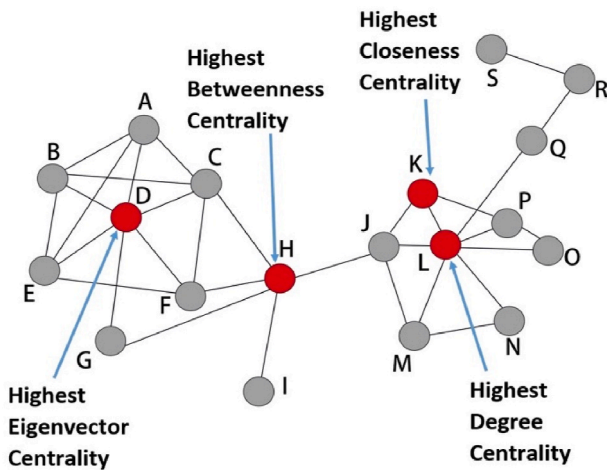


Fig. 2. Illustration of network centrality.

2. **Closeness Centrality** measures the proximity of a node to all other nodes in the network. It is determined by calculating the average shortest path length from the node to all other nodes. The formula is shown in the following equation:

$$C(K) = \frac{(n - 1)}{\sum_{K \neq L} d_G(K, L)} \quad (3)$$

where $d_G(K, L)$ denotes the length of the shortest path between node K and node L , n is the number of nodes and $n - 1$ is a normalizing constant. In Fig. 2, point K is considered to have maximum closeness because its connections have the shortest distance compared to the other point connections. Therefore, closeness centrality could be utilized to measure how rapidly the disease will spread to all other airports (Nikolaou and Dimitriou, 2021).

3. **Betweenness Centrality** measures the importance of a node to the shortest paths through the network. The calculation of betweenness centrality measures is mainly based on the identification and distance of the shortest paths between the airport networks. Thus, in order to calculate these measurements for weighted networks, the shortest paths between airports must be identified (Yang and Knoke, 2001; Du et al., 2015). These paths will form a binary network which is found by minimizing the number of intermediary nodes, and its distance is defined as the fewest ties connecting the two airports. The shortest path between airports is calculated using equation (4).

$$d_{F,J} = \min(x_{FH} + \dots + x_{HJ}) \quad (4)$$

where x_{FH} is defined as 1 if airport F is connected to airport J , while H is the intermediary airport on the path between airport F and J . Then the formula for calculating the betweenness centrality is shown in the equation below:

$$B(H) = \sum_{J \neq F} \frac{\sigma_{JF}(H)}{\sigma_{JF}} \quad (5)$$

where $\sigma_{JF}(H)$ is the number of shortest paths from node J to node F that pass through node H . Point H in Fig. 2, for instance, has the highest level of betweenness centrality because it has the shortest connection path to the important point network and is the transfer point from one network to another (Sun et al., 2020). Thus, if the airport with the highest betweenness, was forced into lockdown, this would disrupt the entire airport network.

4. **Eigenvector Centrality** measures the importance of a node by taking into account the importance of its neighbors (Golbeck, 2013). It

is also used to measure the level of influence of a node within the network because it is based on the concept that links from important nodes are stronger than links from less important nodes. The formula is shown in the following equation:

$$E(D) = \frac{1}{\lambda} \sum_{F \in M(D)} E(F) \quad (6)$$

In which $E(D)$ and $E(F)$ are the relative centrality scores of vertices D and F respectively, λ is the constant eigenvalue, and $F \in M(D)$ denotes that the sum is greater than F such that the nodes D and F are connected. For instance, point D is considered to have the highest eigenvector centrality since it has the strongest connection to the important point (point with the most connections). Thus, the airport with the highest eigenvector value is assumed to be the hub that is connected to another important major hub airports (Li et al., 2021).

4. Results

This section includes a brief account of the clustering and centrality measurements of flight data in Northeast Asia. A more specific explanation will be discussed separately. Then, we will show how the impact of COVID-19 has changed in the various O-D flow clusters and has affected airport popularity.

4.1. Clustering results

In this study, we grouped the O-D flow into eleven clusters based on the silhouette analysis result. These clusters were separated according to local or international flights (local = 0/international = 1), short, medium or long-distance flights (short = 1, medium = 2, long = 3), or whether the flights originated from or are bound for China (departure from China = 0/1, Arrival to China = 0/1). Clusters 1–5 are the O-D flow clusters of flights that have no connection to China, while clusters 6–11 are the ones that do. The impact of COVID-19 in each cluster is illustrated by the changes in the O-D flow before and during the pandemic outbreak, the percentage of O-D flow reduction, and the lower number of passengers. In summary, the clustering results illustrate how COVID-19 has affected O-D flow as well as airport network connectivity. The results were analyzed according to three factors: if the flight is connected to China, if the O-D flow is domestic or international and the flight distance. Then, we were able to measure the impact of COVID-19 based on changes in the O-D flow ratio (the percentage of O-D flow in a cluster compared to the total O-D flow in Northeast Asia) before and during the pandemic outbreak, the reduction in the percentage of O-D flow, and in the percentage of passenger volume.

Our first finding indicated that COVID-19 has had a more devastating impact on the airline O-D flow connected with China than that with no connection. Moreover, we have found that COVID-19 has had a stronger impact on flights going to compared to those originating from China. Prior to the pandemic, the O-D flow related to China dominated airline traffic in Northeast Asia (51.22%) compared to that with no connection (48.78%). However, during the outbreak, the majority of flights were unconnected to China (57.54%). Furthermore, COVID-19 has had a major impact on passenger numbers. For example, there was a drop in O-D flow for flights connected with China that ranged from 14.2% to 82.6%, while the reduction in O-D flow not connected to China ranged from 1.5% to 46.1%. Similarly, the passenger numbers decreased from 70.1% to 98.4% for flights connected to China while this number was reduced by 60%–93.10% for unconnected flights. On the other hand, we also found that the O-D flow of international flights departing from China was reduced by 68.3–68.6%, whereas those headed for China were cut from 77% to 82.6%.

The second finding showed that COVID-19 has had a greater impact on international (cluster 4–9) than on domestic flights (clusters 1–3 and 10–11). Table 3 illustrates that during the outbreak, the total percentage

Table 3
The differences before and during the COVID-19 outbreak in each cluster.

| Cluster No. | Flow Characteristics | Ratio Before | Ratio During | Number of OD Flow | | | Number of Passengers | | |
|-------------|---|--------------|--------------|-------------------|--------|-------------------------|----------------------|-----------|-------------------------|
| | | | | Before | During | Percentage of reduction | Before | During | Percentage of reduction |
| 1 | Domestic (outside China), short flight distance | 31.17% | 43.35% | 738 | 727 | 1.50% | 8,130,211 | 3,255,994 | 60.00% |
| 2 | Domestic (outside China), medium flight distance | 4.86% | 5.25% | 115 | 88 | 23.50% | 566,166 | 225,455 | 60.20% |
| 3 | Domestic (outside China), long flight distance | 0.42% | 0.48% | 10 | 8 | 20.00% | 9,277 | 3,035 | 67.30% |
| 4 | International, short, origin not from China, destination not to China | 6.42% | 4.89% | 152 | 82 | 46.10% | 2,313,504 | 160,189 | 93.10% |
| 5 | International, medium/long, origin not from China, destination not to China | 5.91% | 3.58% | 140 | 60 | 57.10% | 1,776,739 | 71,370 | 96.00% |
| 6 | International, short, originate from China | 2.15% | 0.95% | 51 | 16 | 68.60% | 656,467 | 17,567 | 97.30% |
| 7 | International, medium/long, originate from China | 1.73% | 0.78% | 41 | 13 | 68.30% | 466,780 | 7,387 | 98.40% |
| 8 | International, short, destination to China | 9.92% | 3.22% | 235 | 54 | 77.00% | 1,435,411 | 36,213 | 97.50% |
| 9 | International, medium and long, destination to China | 8.02% | 1.97% | 190 | 33 | 82.60% | 820,983 | 20,273 | 97.50% |
| 10 | China domestic, short flight distance | 19.97% | 24.21% | 473 | 406 | 14.20% | 7,024,330 | 2,096,954 | 70.10% |
| 11 | China domestic, medium, and long flight distance | 9.42% | 11.33% | 223 | 190 | 14.80% | 3,049,326 | 762,235 | 75.00% |

of domestic flights increased (from 65.84% to 84.62%) while that of international flights decreased (from 34.15% to 15.39%). On the other hand, despite the fact that both O-D flow and passenger numbers were decreasing for both domestic and international flights during the outbreak, one must remember that there have been far fewer international flights. During the outbreak, the O-D flow of domestic flights was reduced by 1.5%–23.5%, while that of international flights tumbled even more from 46.1% to 82.6%. Similarly, we also found the reduction in the number of passengers on domestic flights (ranging from 60% to 75%) was much lower than on international flights (ranging from 93.1% to 98.4%).

Our third finding illustrates that COVID-19 has had a stronger impact on the O-D flow of long-distance flights. For example, with regard to domestic flights outside of China (Cluster 1–3), there appeared to be more of a reduction in O-D flow for medium and long-distance flights (20%–23.5%) than for short flights (1.5%). Similarly, due to COVID-19, long-distance international flights unconnected to China declined by 57.1%, while shorter flights were decreased by 46.1% (Cluster 4–5). On the other hand, for the flights destined for China, the long-distance flights had a higher decline in terms of percentage of O-D flow number than the short-distance flights by 82.6% and 77% respectively. Furthermore, there have been fewer passengers on both domestic and international long-distance flights. More specifically, the differences in passenger numbers between short and long-distance domestic flights outside of China was 7.3 percent (ranging from 60 to 67.3%). For international flights with no connection to China, the percentage was 2.9% (ranging from 93.1% to 96%). This finding was also true of flights connected to China; however, it must be noted that flight distance was less of a factor for international flights not connected to China due to the travel ban that was enforced in most of the countries regardless of distance. For example, the percentage of passengers on short-distance international flights connected to China (97.3%) was almost identical to medium and long-distance flights (98.4%).

4.2. The results from network centrality metrics

4.2.1. Statistical significance via centrality metrics

For this study, several statistical tests were conducted via centrality metrics to measure the effect of COVID-19 on airport networks. These tests were implemented on all airports and the top 30 hubs in Northeast Asia separately to determine if COVID-19 has affected the international and local airports differently. First, we used the paired *t*-test to validate the differences among the centrality measurements before and during the COVID-19 outbreak (Table 4) by obtaining an average of the

Table 4
Paired *t*-test results for the centrality metrics.

| All Airports | | | | | |
|---------------------|-----------------|-----------------|------------|--------------------------|------------|
| Metrics | Before | During | Difference | Percentage of Difference | P-value |
| Degree | 13.8 ± 26.6 | 9.9 ± 19.2 | -3.95 | -28.6% | 5.2E-13*** |
| Closeness | 9.8E-4 ± 1.6E-4 | 1.1E-3 ± 1.8E-4 | 1.05E-4 | 10.7% | 2.3E-16*** |
| Eigenvalue | 0.1 ± 0.02 | 0.06 ± 0.1 | -0.07 | -70% | 2.3E-16*** |
| Betweenness | 339.4 ± 1319.7 | 412.5 ± 1722.8 | 73.17 | 21.5% | 0.16 |
| Top 30 Hub Airports | | | | | |
| Metrics | Before | During | Difference | Percentage of Difference | P-value |
| Degree | 85.6 ± 45.5 | 58.6 ± 37.8 | -27 | -31.5% | 3.5E-08*** |
| Closeness | 1.7E-3 ± 9.0E-5 | 1.9E-3 ± 8.0E-5 | 1.89E-4 | 11.1% | 8.6E-12*** |
| Eigenvector | 0.5 ± 0.2 | 0.3 ± 0.3 | -0.23 | -46% | 3.5E-05*** |
| Betweenness | 3358.5 ± 3055.6 | 3956.6 ± 4314.6 | 597.96 | 17.8% | 0.31 |

centrality. This was followed by determining the p-value of the paired *t*-test. Second, the Wilcoxon signed-rank test was implemented to explore the changes in airport ranking based on the centrality metrics results before and during the pandemic outbreak (Table 5). The results included the number of airports that increased in rank (Before > During) as well as those that fell (Before < During) in each centrality metric, followed by

Table 5
Wilcoxon signed-rank test result on centrality metrics of all airports.

| All Airports | | | | |
|---------------------|-----------------|-----------------|---------|-----------|
| Metrics | Before > During | Before < During | Z-value | P-value |
| Degree | 199 | 137 | -1.725 | 0.085 |
| Closeness | 218 | 119 | -4.794 | 0.0001*** |
| Eigenvector | 187 | 151 | -1.864 | 0.062 |
| Betweenness | 222 | 110 | -3.782 | 0.0001*** |
| Top 30 Hub Airports | | | | |
| Metrics | Before > During | Before < During | Z-value | P-value |
| Degree | 15 | 12 | -0.072 | 0.942 |
| Closeness | 8 | 22 | -2.897 | 0.004** |
| Eigenvector | 9 | 20 | -2.628 | 0.009** |
| Betweenness | 13 | 17 | -1.102 | 0.270 |

Significant Code: 0.001***; 0.01**; 0.05*; 0.1*

the coefficient (Z-value) and its P-value. The following sections describe how each centrality metric (degree, closeness, eigenvector, and betweenness centrality) value and ranking changed in every airport during COVID-19 (Table 6). The orange sections in the table indicate a rise in rank, while the blue sections signify a decline. The darker sections denote a much more significant change in rank than do the lighter ones.

4.2.2. COVID-19's impact on the centrality metrics values

a. Degree centrality

The results in Table 4 illustrate that COVID-19 significantly reduced the degree centrality values of all airports, particularly the 30 largest hubs. Before the COVID-19 outbreak, the average degree centrality metric of all airports was 13.83 which indicates that each airport had approximately 13–14 inbound and outbound line. During the outbreak, the mean value of degree centrality in all airports dropped by 28.6%, and the average O-D flow in each airport decreased to 9.88. For the top 30 hubs, the average degree centrality value was higher than that of all the airports. The average degree centrality fell by 31.5% of O-D flow from 85.6 to 58.6. For instance, in December 2019, the airport with the highest degree of centrality was Shanghai Pudong International Airport (PVG) with 200 inbound and outbound flights. However, during the pandemic outbreaks, the flights were decreased by half. Similarly, Beijing Capital International Airport (PEK) which had 195 inbound and outbound flights pre-pandemic, was reduced to 126. However, for non-major hub airports, such as Sendai Airport (SDJ) in Japan, the degree metrics value only decreased by 7, from 31 to 24. This result indicated that COVID-19 had a greater impact on major hub airports than on smaller airports.

b. Closeness centrality

The paired *t*-test results for the closeness metric showed that COVID-

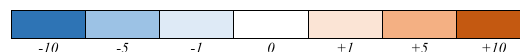
19 significantly increase the metric value during the outbreak in all airports and the top 30 hubs. As seen in Table 4, the majority of all the airports had an average closeness value of approximately 0.00098 in December 2019, which increased to 0.00108 in April 2020. Similarly, the closeness value of the top 30 hubs also increased from 0.00126 to 0.00144 in April 2020. This result indicates that during the outbreak, there were fewer long-distance flights both at all airports and the top 30 hubs. This may be due to the lockdowns and restrictions in certain countries that limit long-haul or international flights (Bauer et al., 2020; Lau et al., 2020; Suzumura et al., 2020) in an effort to halt disease spread. Due to the fact that many airports limited long-haul or international flights during the pandemic, there were more airport connections with closer distances during this time which resulting a decrease in the flight distance by 10.7%–11.1% during the pandemic. Furthermore, travelers who still wished to fly long distance must factor in the possibility of having more transit airports (Zhang et al., 2022) compared to before the pandemic.

c. Eigenvector centrality

According to the results in Table 4, COVID-19 also significantly reduces the average eigenvector value. In December 2019, the average eigenvector value of all airports was 0.136; however, in April 2020 it decreased to 0.063. Furthermore, the average of the top 30 hubs also decreased from December 2019 (0.49) to April 2020 (0.26). For example, the eigenvector value of Incheon International Airport (ICN) fell from 0.983 to 0.666 during the COVID-19 outbreak. According to Zhang et al. (2020), COVID-19 has had a greater impact on major hub airports due to a reduction in connections during the pandemic in an effort to prevent the virus from spreading. Therefore, some airports that have suspended connections to major hubs may have a significant reduction in eigenvector values, ranging from –46% to –70%. This will influence travel in smaller cities due to flight bans from major hubs airports to other smaller airports (Sanchez et al., 2020).

Table 6
Top 30 rankings based on the centrality metrics results for Northeast Asia.

| Rank | Before COVID-19 | | | | During COVID-19 | | | |
|------|-----------------|------------------|-------------|--------------|-----------------|------------------|-------------|---------------|
| | degree | closeness | eigenvector | betweenness | degree | closeness | eigenvector | betweenness |
| 1 | PVG(200) | PVG(0.00151) | NRT(1) | PEK(14256.2) | PVG(150) | PEK(0.00173) | HND(1) | HND(17692.06) |
| 2 | PEK(195) | CAN(0.00147) | ICN(0.983) | HND(9325.28) | CAN(141) | PVG(0.00164) | NRT(0.909) | VVO(12119.74) |
| 3 | CAN(167) | PEK(0.00144) | PVG(0.949) | PVG(8233.91) | PEK(126) | CAN(0.00160) | OKA(0.874) | ICN(11522.86) |
| 4 | SZX(145) | HND(0.00141) | TPE(0.947) | OVB(6550.65) | SZX(126) | ICN(0.00150) | FUK(0.869) | PVG(11119.79) |
| 5 | TPE(124) | ICN(0.00138) | FUK(0.902) | ICN(5689.78) | HND(111) | HKG(0.00148) | KIX(0.814) | CAN(8150.19) |
| 6 | HND(115) | NRT(0.00136) | CTS(0.887) | IKT(5316.73) | NRT(76) | SZX(0.00147) | CTS(0.794) | PEK(7243.92) |
| 7 | ICN(113) | SZX(0.00134) | HND(0.886) | CAN(4985.90) | SHA(74) | NRT(0.00144) | NGO(0.754) | NRT(7064.89) |
| 8 | HKG(103) | KIX(0.00130) | OKA(0.882) | NRT(4611.02) | WUH(69) | TPE(0.00144) | TPE(0.703) | OVB(6118.01) |
| 9 | KIX(102) | TPE(0.00127) | KIX(0.876) | HKG(4246.74) | FUK(64) | KIX(0.00141) | ICN(0.666) | ULN(4859.04) |
| 10 | WUH(102) | HRB(0.00126) | HKG(0.872) | CJU(3408.21) | CTS(62) | SHA(0.00141) | ITM(0.645) | UUS(3793.75) |
| 11 | NRT(100) | TAO(0.00123) | PEK(0.822) | KJA(3258.12) | ICN(62) | WUH(0.00140) | KOJ(0.537) | IKT(3326.46) |
| 12 | SHA(98) | WUH(0.00122) | NGO(0.788) | ULN(3135.73) | OVB(62) | HND(0.00139) | PVG(0.533) | TPE(3268.68) |
| 13 | CTS(85) | HKG(0.00121) | PUS(0.662) | TPE(2856.33) | OKA(60) | NGO(0.00136) | SDJ(0.487) | KHV(3258.33) |
| 14 | FUK(81) | KHH(0.00121) | KHH(0.613) | FUK(2844.26) | KIX(59) | CTS(0.00133) | MYJ(0.454) | SVX(3015.29) |
| 15 | NGO(78) | XMN(0.00121) | NKG(0.607) | CTS(2829.92) | TPE(56) | FUK(0.00133) | KLI(0.421) | KJA(2992.06) |
| 16 | OKA(73) | SHA(0.00121) | TAO(0.600) | UUS(2226.82) | ITM(52) | PUS(0.00131) | KHH(0.394) | CJU(2890.19) |
| 17 | OVB(70) | SHE(0.00120) | DLC(0.598) | VVO(2211.87) | NGO(48) | MFM(0.0013) | KMI(0.381) | KIX(2482.43) |
| 18 | CJU(62) | NGO(0.00119) | HGH(0.580) | YKS(2058.81) | KJA(40) | VVO(0.00131) | KMI(0.378) | FUK(2202.14) |
| 19 | IKT(59) | CTS(0.00119) | XIY(0.556) | KIX(1911.29) | CJU(37) | SYX(0.00131) | PEK(0.375) | TSA(2176.73) |
| 20 | ITM(56) | CTU(0.00118) | KOJ(0.544) | KOJ(1890.71) | IKT(37) | HRB(0.00131) | KMQ(0.363) | CTS(2160.49) |
| 21 | MFM(56) | DLC(0.00118) | CAN(0.544) | SZX(1875.59) | SVX(37) | KHH(0.00131) | NGS(0.355) | KHH(1967.04) |
| 22 | KJA(53) | NGB(0.00117) | TSN(0.535) | OKA(1650.11) | KOJ(36) | OKA(0.00131) | HKG(0.337) | SZX(1871.93) |
| 23 | PUS(52) | MFM(0.001165501) | NGB(0.532) | SVX(1648.20) | VVO(32) | CTU(0.00130039) | ISG(0.336) | KOJ(1862.18) |
| 24 | KHH(50) | TSN(0.001165501) | SDJ(0.521) | TSA(1642.87) | KHH(26) | XIY(0.001293661) | UKB(0.332) | ITM(1429.92) |
| 25 | VVO(45) | SYX(0.001165501) | WUH(0.515) | ITM(1584.83) | HKG(25) | HFE(0.001287001) | ASJ(0.318) | OKA(1368.44) |
| 26 | KOJ(42) | WEH(0.001162791) | FOC(0.508) | SHA(1361.64) | KHV(24) | TAO(0.00128041) | TAO(0.315) | PUS(1216.79) |
| 27 | SVX(40) | YNT(0.001162791) | MEM(0.493) | NGO(1270.60) | SDJ(24) | IKT(0.001278772) | CAN(0.308) | GMP(1026.14) |
| 28 | YKS(40) | XIY(0.001162791) | MYJ(0.492) | HMA(1223.16) | ULN(23) | DLC(0.001278772) | KCZ(0.306) | HMA(982.26) |
| 29 | SDJ(31) | FOC(0.001158749) | CTU(0.488) | WUH(1179.17) | HMA(22) | NKG(0.00127551) | PUS(0.295) | NGO(829.83) |
| 30 | TSA(31) | CKG(0.001157407) | CSX(0.486) | HKD(1043.58) | SGC(22) | HGH(0.001273885) | XMN(0.279) | HKD(806.82) |



d. Betweenness centrality

Betweenness centrality measures the extent to which an airport is utilized as a transfer point. Intuitively, the higher the betweenness centrality, the more likely passengers will be to use an airport as a transfer hub. During the pandemic, the average betweenness value of all airports and the top 30 airports increased by 21.5% and 17.8%, respectively. The main reason for this is that some of the largest transfer hubs have been practically shut down, increasing the importance of other airports betweenness in the network. However, according to the paired *t*-test results, this change had no significant effect on the betweenness centrality trend for all airports or the top 30 hub networks. This result indicates that the transfer airport trend is relatively stable.

4.2.3. The impact of COVID-19 on the ranking of centrality metrics

a. Degree centrality

As shown in Table 5, the Wilcoxon signed-rank test indicated that COVID-19 considerably changed the 90% confidence level of the all-airport data; however, the degree centrality ranking of the top 30 hubs did not change significantly during the COVID-19 outbreaks. Overall, there was a drop in the rankings of 199 airports and an increase in 137 during COVID-19. Even though the top 30 hubs experienced a similar trend to that of all the airports, these increases and decreases were not significant. As shown in Table 6, this result is indicated by the dominance of lighter colors with regard to the degree centrality. For example, also shown in Table 6, the highest values were all associated with airports in China, specifically Shanghai (PVG) Airport in December 2019, followed by Beijing (PEK) Airport. The third and fourth highest were associated with Guangzhou (CAN) and Shenzhen (SZX), respectively. These rankings were followed by airports in Taiwan, Japan, South Korea, and Hong Kong. In April 2020, the rankings of the top 10 airports changed very little with the exception of Hong Kong (HKG) and Taipei (TPE) airports which fell significantly. Shanghai (PVG) remains the highest-ranked, the second is Guangzhou (CAN) followed by Shenzhen (SZX) and Beijing (PEK). However, Hong Kong (HKG) and Taipei (TPE) airports have dropped from the top 10 status into the top 30. A significant change in ranking also occurred in the lower positioned airports, some of which shifted from top five to top ten. This happened because of the wide gap between the top 10 airports and the others. Even though the O-D flow decreased to a greater extent in the top 30 hub airports, the popularity rankings of the top 10 airports changed only slightly.

b. Closeness centrality

According to the results of the Wilcoxon signed-rank test, there was a significant change at the 99% confidence level for all airports as well as the top 30 hubs during the COVID-19 outbreak. In general, the rankings of 218 airports fell during the quarantine, while only 119 rose. However, the number of airport hubs that increased in the rankings outnumbered those that fell. Table 6 shows that prior to the COVID-19 outbreak, the top three rankings were held by Chinese airports, a trend that has continued to this day. The Incheon Airport (ICN) in South Korea rose to fourth place, and the Hong Kong Airport (HKG) jumped from 13 to five during the outbreak. We also discovered that airports that implemented total international flight restrictions, such as Vladivostok Airport (VVO) and Irkutsk Airport (IKT) in Russia, increased their rankings even more than those that only banned specific international flights, such as Incheon Airport (ICN) in South Korea. This is expected because the number of operating airports and international flights decreased which impacted the closeness rankings in the airport network during the outbreak.

c. Eigenvector centrality

According to the Wilcoxon signed-rank test, there was a significant change at the 90% confidence level in the data for all airports and a significant change at the 99% confidence level for the top 30 hubs during the COVID-19 outbreak. It must be noted that the latter was an inverse trend in which the number of airports that rose in the ranking was much higher than those that dropped. The results show that 87 airports dropped in rank while 151 rose during this time. The results illustrated in Table 6 show that several smaller airports, such as Osaka Airport (ITM), Matsuyama Airport, Niigata Airport (KIJ), and others, increased in rank significantly. Meanwhile, several hubs, such as Beijing Airport (PEK), Shanghai Airport (PVG), and Incheon Airport (ICN), had a significant drop in rankings, which could be due to the suspension of the O-D flow between these top hubs. On the other hand, if the smaller airports remained connected to their hub airports, this may have led to less of a decrease in their eigenvector centrality than that of the top 30 hub airports. Thus, several smaller airports moved into the top 30 due to an increase in their eigenvector ranking, while the hub airports experienced a drop in rank.

d. Betweenness centrality

As previously stated, there was a significant change at the 99% confidence level in the all-airport data; however, the betweenness centrality ranking of the top 30 hubs did not change significantly during the COVID-19 outbreaks. A higher ranking with regard to betweenness centrality illustrates the popularity of the airport as a transit hub in its country. For example, in December 2019, Beijing (PEK), Shanghai (PVG), and Guangzhou (CAN) airports were the top transfer hubs in China. Similarly, Incheon Airport (ICN) was regarded as the top transfer hub in South Korea, and Tokyo Haneda (HND) and Narita Airport (NRT) were the most popular in Japan, as were Taoyuan Airport (TPE) in Taiwan, and Novosibirsk Airport (OVB) in Russia. This trend has continued throughout the pandemic with the exception of Russia where Vladivostok Airport (VVO) became the highest-ranked hub due to the fact that Russia was the only country to impose restrictions on all international flights. As a result, their airport network changed significantly, as did the top transfer hubs.

In general, the statistical test showed significant differences in the number and popularity ranking of all airports centrality metrics. However, for the top 30 hub airports, even though the values of the centrality metrics have changed considerably, the popularity ranking based on the centrality and betweenness degree did not significantly change during the outbreak. According to the paired *t*-test results, most of the centrality metrics showed a significantly negative difference with a 95% confidence level in both all airports and the top 30 hubs. Among all the metrics, the degree of centrality, closeness, and eigenvector centrality have shown significant differences during the outbreak. In other words, this difference illustrates a significant decrease in the O-D flow and in the airport network in general. However, the betweenness metric showed an insignificant *p*-value of 0.1636 which indicates there has been no significant change in popular transfer airports.

In terms of airport popularity rankings, the Wilcoxon signed-rank test also showed a significant change in the ranking of all the airports, but the popularity ranking of the top 30 hub airports did not change significantly in degree and betweenness centrality ranking before and during COVID-19. For the all-airport dataset, the degree of centrality and eigenvector centrality were significantly different with a 90% confidence level while the closeness and betweenness metric had a higher confidence level of 99%. The change in popularity ranking mostly occurred in the non-hub airports with lower O-D flow.

5. Discussion and conclusion

This study utilized the CLARA algorithm and centrality metrics to analyze the various impacts of COVID-19 on airline O-D flow and airport network. The results show a heterogeneous change in terms of O-D flow

patterns and passenger numbers during the COVID-19 outbreak. In addition, centrality metrics also show a significant difference in the number and the ranking of all the airport's centrality metrics.

5.1. Clustering analysis

Our findings showed that COVID-19 has had a stronger impact on airline O-D flow connected to China compared to that with no connection. Before the COVID-19 outbreak, the total percentage of the O-D flow of air traffic connected to China was higher than that with no connection. However, in response to the pandemic, several countries, including Japan, Russia, Taiwan, and China, began implementing strict flight restrictions on international routes beginning in January 2020 (Åslund, 2020; Inoue, 2020; Lin et al., 2020; Zhang et al., 2020). Thus, the percentage of O-D flow unconnected to China exceeded that connected to it. This result is consistent with the findings of previous studies which indicate that COVID-19 has had a serious impact on international flights, particularly on routes originating and leaving from China (Lau et al., 2020; Suzumura et al., 2020). As previously stated, this may be the result of the travel ban (Erkhembayar et al., 2020) which has caused disruption of the O-D flow and a major decrease in the number of passengers.

Our second finding implies that COVID-19 has also had more impact on international than domestic flights in that after the outbreak, the ratio of domestic flights increased while that of international flights decreased. The reduction in the number of international flights was caused by the international travel ban imposed by many countries (Chinazzi et al., 2020) to prevent COVID-19 infection (Zhang et al., 2020). As a result, travel restrictions had a serious effect on the trends of international flight networks around the world (Suzumura et al., 2020). According to our results, the increase in the percentage of domestic flights indicated that local aviation has begun to recover, particularly in China. According to Dube et al. (2021), Chinese domestic O-D flow began to improve in February. This recovery has been sustained, with most airports making consistent gains throughout the year. As the passenger numbers, although the pandemic has significantly reduced the number of passengers on both domestic and international flights, international flights were affected to a greater extent. This finding is consistent with a previous study by Lau et al. (2020), who found a reduction in passenger numbers during the COVID-19 outbreak. They also found that the number of passengers on domestic flights outnumbered those on international flights during the COVID-19 outbreak period in China.

Furthermore, the O-D flow has been reduced with regard to different flight distances. According to clustering results, COVID-19 appeared to reduce the number of short-domestic flights outside of China compared to medium and long-distance flights. Similarly, COVID-19 has had a greater impact on long-distance international flights unconnected to China than on shorter flights. This finding is consistent with those of Khanh et al. (2020), who discovered that the increased risk of onboard transmission of COVID-19 during long flights has the potential to cause large COVID-19 clusters. Our findings may reflect the reduction in the number of long-distance international flights that is backed up by our cluster results. However, it is interesting that flight distance does not appear to have had a noteworthy impact on the reduction of the O-D flow of domestic flights of China. Since the COVID-19 outbreak originated in Wuhan, China, and was predicted to spread to nearby areas (Chinazzi et al., 2020), this finding deserves further analysis in the future.

Compared to other continents, Sun et al. (2021b), discovered that the impact of COVID-19 on airports in the United States has been rather homogeneous, with most airports only partially affected. Those along the coasts have been slightly more affected, usually due to halted intercontinental connections to Asia on the West Coast and Europe on the East Coast. In Europe, COVID-19 has had a much stronger impact on the majority of large airports, especially in Central Europe. There are,

however, many smaller airports, particularly in the south, that have fared better. To compensate for losses in 2020, these airports must have been able to attract significant numbers of tourists in the summer of that year. The impact on airports in Northeast Asia is somewhat similar to those in the United States, with many only partially affected. The top international hubs and politically significant economic centers have experienced significant flight reductions. On the other hand, China began an early and vigorous effort to recover domestic tourism, in part to stimulate the local economy.

5.2. Centrality metrics analysis

In terms of the airport networks, there was a significant difference in the value of the centrality metrics of all airports with the exception of betweenness centrality due to variations in the severity of flight restrictions. The impact of COVID-19 was clear in the decrease of the value of centrality metrics for all airports during the pandemic, particularly for the top ten hub airports, among which Taoyuan (TPE), Beijing (PEK), and Hong Kong International Airport (HKG) decreased the most in April 2020. This occurred as a result of Taiwan's, and Hong Kong's strict travel restrictions, which only allow their citizens to return home with a special permit (Lin et al., 2020). Thus, the connectivity of these has been significantly reduced. On the other hand, the pandemic had no significant effect on the betweenness centrality. Several airports, such as Incheon Airport (ICN), experienced an increase in the betweenness centrality values, while others in Russia, such as Novosibirsk Airport (OVB), have had a decrease. This occurred because several countries like South Korea only enacted a travel ban to China, while others such as Russia banned all international flights, especially involving countries with high infection rates (Reshetnikov et al., 2020). Hence, the importance and popularity of some airports in the networks have increased or changed during the outbreak (Sun et al., 2020).

Even though the centrality metrics values changed significantly, the Wilcoxon signed-rank test indicated that the degree and betweenness centrality ranking of the top 30 hubs have not. Interestingly, based on degree centrality metrics, several airports in China have maintained their top 4 ranking despite the outbreak. Our findings showed that this occurred due to the significant gaps in degree centrality values with regard to the top 10 airports. Thus, even though there has been more of a decrease in the O-D flow in the top 30 hub airports because they are more likely to transport infected passengers via transfer flights (Lu et al., 2021), their popularity ranking in the top 10 airports has remained approximately the same. We also found that Shanghai Airport (PVG), which was consistently ranked in the top ten for every degree prior to COVID-19, has been on a downward spiral during the pandemic. The drop in rank of several hub airports, such as Shanghai (PVG), Taoyuan (TPE), and Hong Kong Airports (HKG), may raise the rank of lower airports and affect the overall ranking of the airport network (Voltes Dorta et al., 2017). The rankings have changed significantly due to the flight restrictions implemented in several airports, particularly those in China, in an attempt to prevent or reduce COVID-19 transmission. Hence, this has increased the importance of some other airports in the networks and has changed their ranking of centrality (Sun et al., 2020).

Authorship contributions

Pei-Fen Kuo: Conceptualization, Methodology, Formal analysis. Writing - Review & Editing, Supervision. I Gede Brawiswa Putra: Methodology, Formal analysis, Validation, Writing - Original Draft, Writing - Review & Editing, Visualization. Faizal Azmi Setiawan: Software, Validation, Formal analysis, Writing - Original Draft, Visualization. Tzai-Hung Wen: Writing - Review & Editing, Supervision. Chui-Sheng Chiu: Data Curation. Umroh Dian Sulistyah: Writing - Original Draft, Writing - Review & Editing.

Declaration of competing interest

The authors whose names are listed immediately below certify that they have **NO** affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; participation in speakers’ bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or

professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

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Appendix A

Cluster 1: Short-distance domestic flights with no origins or destinations in China.

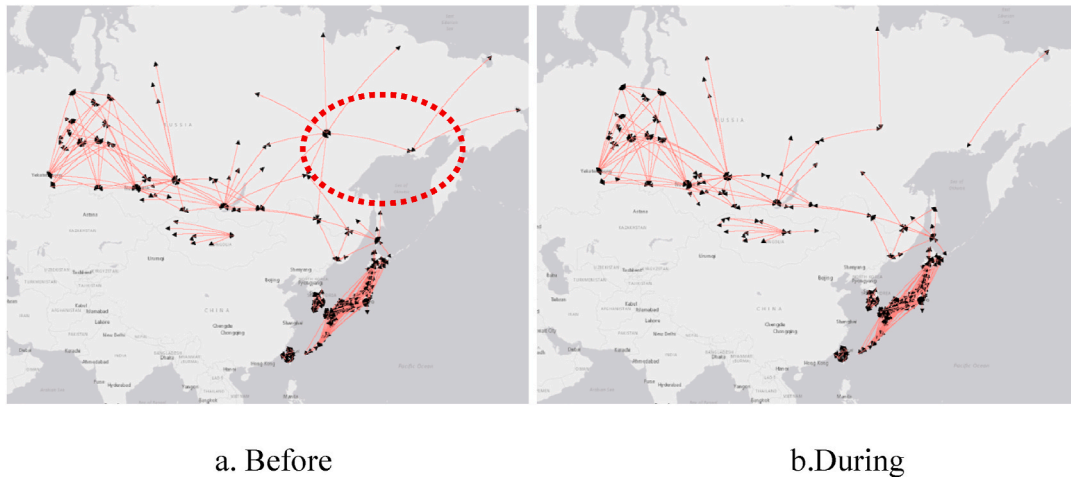


Fig. A. Cluster 1 O-D flow patterns before and during COVID-19 outbreak. a. Before b.During.

In cluster 1, all flow was in the form of short-distance domestic flights (1,100 km–1,500 km) occurring in Japan, South Korea, Mongolia, Russia, and Taiwan. In this cluster, there were 738 routes pre-COVID-19, which decreased by 1.5%–727 during the outbreak. As shown in Fig. A, although some flights in the eastern part of Russia were eliminated, more new routes were introduced in the central and southern parts of Russia during the outbreak. Thus, COVID-19 has had an insignificant effect on the number of short-distance domestic flights. However, it has reduced the passenger volume to nearly 60% (from 8,130,211 to 3,255,994, Table 3).

Cluster 2: Medium-distance domestic flights with no origins or destinations in China.

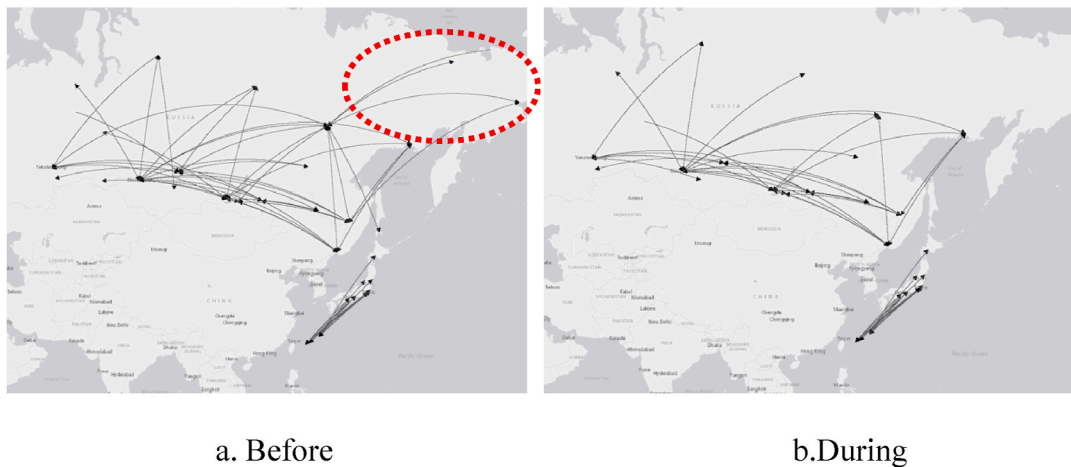


Fig. B. Cluster 2 O-D flow patterns before and during the outbreak. a. Before b.During.

In cluster 2, all airline flow was made up of medium-distance domestic flights (1,500 km–4,100 km) that departed from Russia and Japan. There were 115 routes before COVID-19 and 88 routes during the outbreak, a decrease of 23.5% (Table 3). The most significant difference in airline flow before and during the outbreak was that some domestic routes in Russia were canceled (Fig. B). In addition, COVID-19 also reduced the passenger volume by approximately 60.2% (Table 3).

Cluster 3: Long-distance domestic flights with no connection to China.

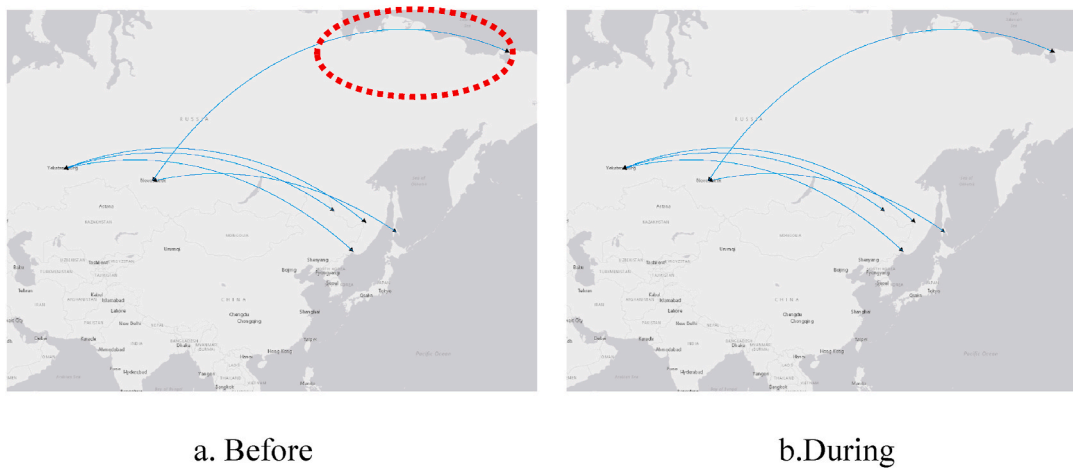


Fig. C. Cluster 3 O-D flow patterns before and during the COVID-19 outbreak.
a. Before b. During.

In cluster 3, all airline flow was made up of long-distance domestic flights in Russia. The number of routes was decreased by 20% from 10 to 8 during the outbreak. According to Fig. C, only the longest route from Novosibirsk (OVB) to Pevek (PWE) in Russia was canceled. In addition, the total passenger volume decreased by 67.3% from 9,277 to 3,035 (Table 3).

Cluster 4: Short-distance international flights with no origin or destination flights from or to China.



Fig. D. Cluster 4 O-D flow patterns before and during the COVID-19 outbreak.
a. Before b. During.

In cluster 4, all airline flow was short-distance international flights. The number of routes were decreased by approximately 46.1% from 152 to 82 during the outbreak. As seen in Fig. D, routes to some airports in Japan were canceled. In addition, the total passenger volume decreased by nearly 93.1% from 2,313,504 to 160,189 (Table 3). Therefore, COVID-19 reduced the number of flights and passengers in cluster 4.

Cluster 5: Medium-and long-distance international flights that have no connection with China.

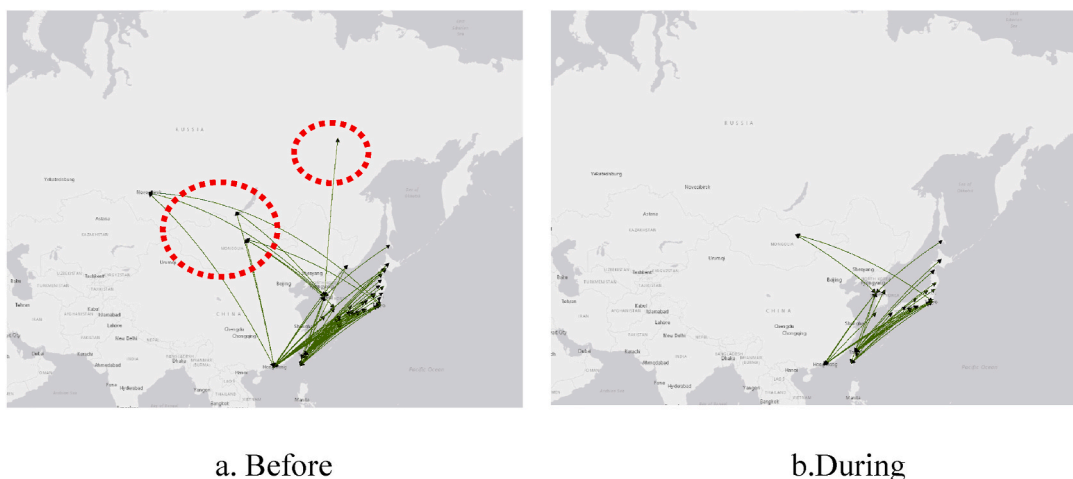


Fig. E. Cluster 5 O-D flow patterns before and during the COVID-19 outbreak.a. Before b.During.

In cluster 5, all flow consisted of medium-to long-distance international flights. The number of routes was decreased by approximately 57.1% from 140 to 60. As seen in Fig. E, all long-distance flights arriving at Russian airports were canceled during the outbreak, which means there was a flight ban in particular airports in Russia. In addition, the total passenger volume decreased by roughly 96% from 1,776,739 to 71,370 (Table 3).

Cluster 6: Short-distance international flights originating from China.



a. Before

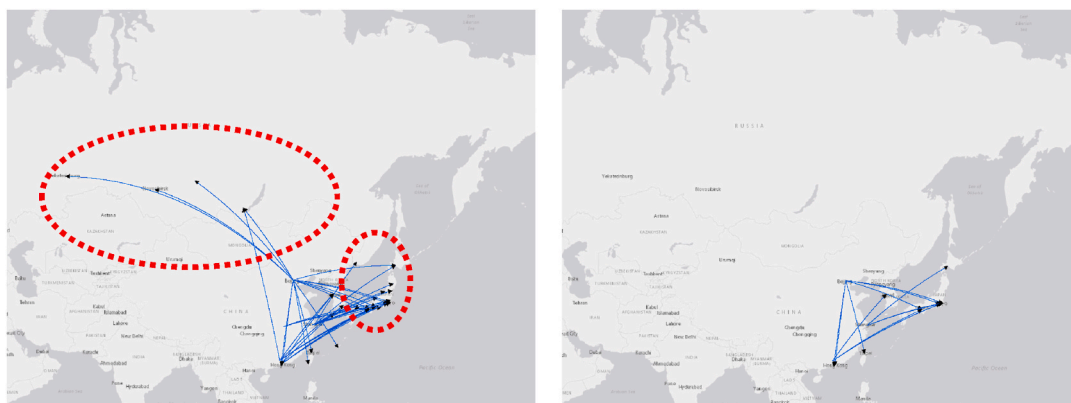
b.During

Fig. F. Cluster 6 O-D flow patterns before and during the COVID-19 outbreak.

a. Before b.During.

In cluster 6, all airline flow included short-distance international flights that departed only from China. Before COVID-19, this cluster had 51 routes that were limited to 16. Fig. F shows that all the flight routes from Wuhan Airport (WUH) were canceled and the flight routes from other airports such as Beijing (PEK), Shanghai (PVG), and Shenzhen (SZX) were severely limited during the outbreak. The total passenger volume also decreased by 97.3% from 656,467 to 17,567 (Table 3).

Cluster 7: Medium-distance international flights originating from China.



a. Before

b.During

Fig. G. Cluster 7 O-D flow patterns before and during the COVID-19 outbreak.

a. Before b.During.

In cluster 7, all airline flow consisted of medium-distance international flights all departing from China. The number of routes decreased by approximately 68.3% from 41 to 13 during the outbreak. As seen in Fig. G, all medium-distance flights originating from Beijing (PEK), Shanghai (PVG), and Guangzhou (CAN) and going to Russian cities such as Krasnoyarsk (KJA), Yekaterinburg (SVX), Vladivostok (VVO), Irkutsk (IKT), Novosibirsk (OVB), and Irkutsk (IKT) were canceled, and flights from China to other airports such as Osaka (KIX), Okinawa (OKA), Sendai (SDJ), Busan (PUS), Jeju (CJU) and Kaohsiung (KHH) were greatly reduced in reaction to the spread of COVID-19. In addition, the total passenger volume decreased by approximately 98.4% from 466,780 to 7,387 (Table 3).

Cluster 8: Short-distance international flights to China.



Fig. H. Cluster 8 O-D flow patterns before and during the COVID-19 outbreak. a. Before b.During.

In cluster 8, all airline flow consisted of short-distance international flights departing from Japan, North Korea, South Korea, Macau, Hongkong, Taiwan, Mongolia as well as Russia to China only. Before COVID-19, this cluster had 235 routes which were drastically limited to 54 during COVID-19 struck. Routes decreased by approximately 77%. This huge difference in the number of routes can be seen in Fig. H, which indicates that many routes from origin countries mentioned at the beginning of the paragraph were canceled during the COVID-19 outbreak. Thus, there were fewer people taking international flights to China during COVID-19 began to spread. In addition, the total passenger volume decreased by nearly 97.5% from 1,435,411 to 36,213 (Table 3).

Cluster 9: Medium-and long-distance international flights not originating from China but with China as a destination.

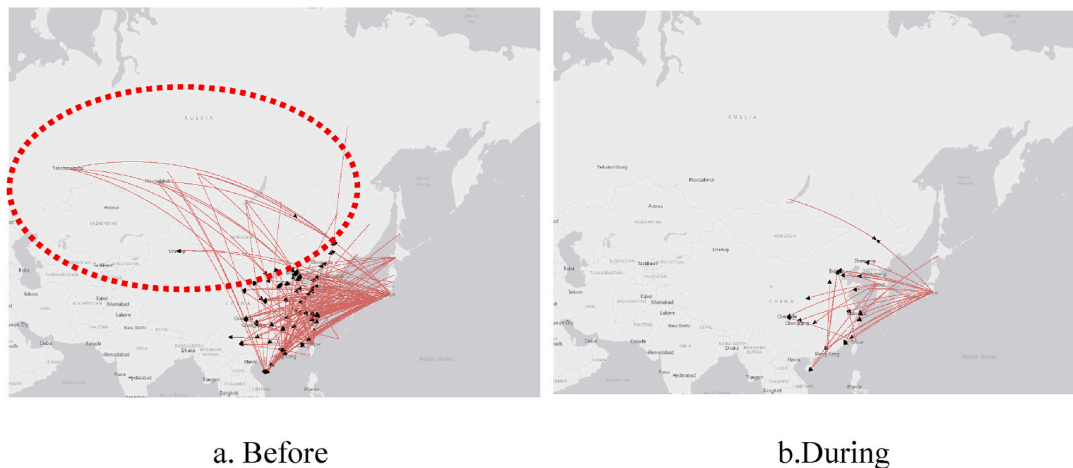


Fig. I. Cluster 9 O-D flow patterns before and during the COVID-19 outbreak. a. Before b.During.

In cluster 9, the airline flow consisted of medium-and long-distance international flights (4,100–4,800 km) departing from several countries such as Japan, South Korea, Macau, Taiwan, Hong Kong, and Russia. In this cluster, there were 190 international routes before the pandemic, which decreased to 33 during the outbreak. The number of routes were reduced by approximately 82.6% in this time period. Fig. I shows that most flights from Hong Kong, Macau, and Taiwan were canceled during COVID-19 struck. Moreover, all flights originating from Russia were also canceled. This indicates that these countries implemented very restricted flight laws. Thus, the number of routes during COVID-19 began to spread was greatly reduced. Additionally, the total passenger volume drastically decreased by almost 97.5% from 820,983 to 20,273 during the outbreak (Table 3).

Cluster 10: Short-distance domestic flights originating from and bound for China.

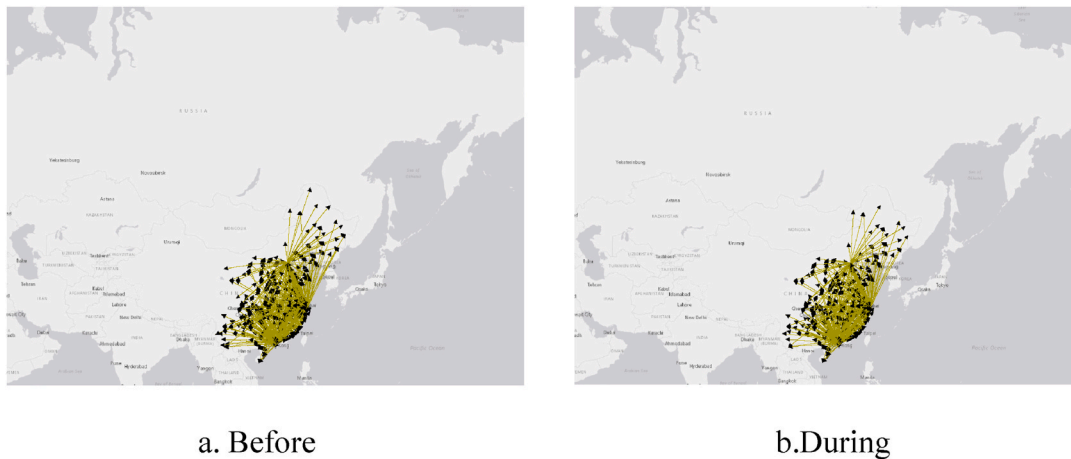


Fig. J. Cluster 10 O-D flow patterns before and during the COVID-19 outbreak.
a. Before b.During.

In cluster 10, all flow patterns were made up of short-distance domestic flights in China (Fig. J). The number of routes slightly decreased by 14.2% from 473 to 406 before and during the outbreak, respectively. Thus, although COVID-19 had only a slight impact on domestic flight routes, it had a huge effect on the passenger volume which decreased by 75% from 5,736,121 to 1,637,755 (Table 3).

Cluster 11: Medium-and long-distance domestic flights originating from and going to China.

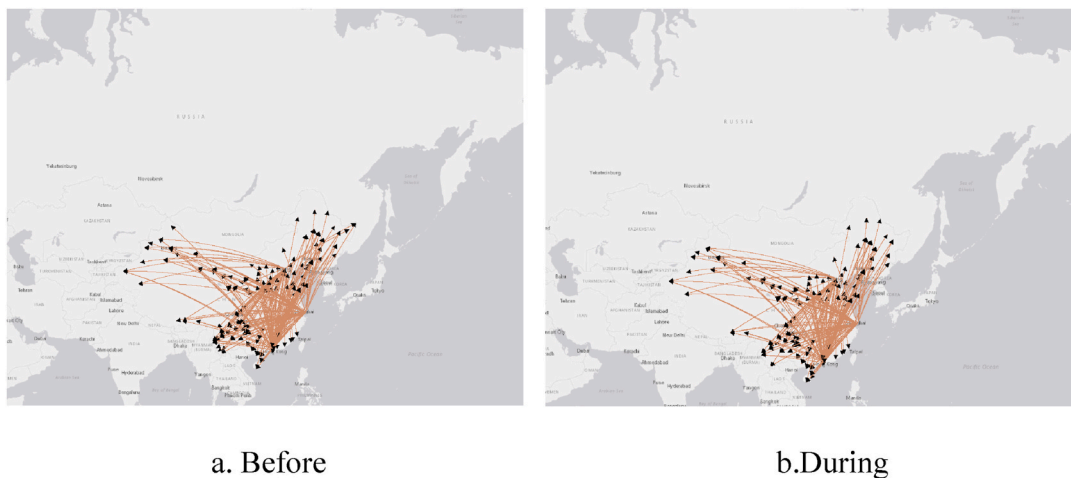


Fig. K. Cluster 11 O-D flow patterns before and during the COVID-19 outbreak.
a. Before b.During.

In cluster 11, all flow patterns consisted of medium-distance domestic flights in China. There were 223 domestic routes before the outbreak; however, these numbers slightly decreased by nearly 14.8% to 190 routes during. Thus, as shown in Fig. K, the impact of COVID-19 on these flights was also insignificant. However, the passenger volume decreased by nearly 75% from 3,049,326 to 762,235 (Table 3).

Appendix B. IATA Airport Code

| IATA code | Airport Name | City | Country | Latitude. | Longitude. | Timezone |
|-----------|--|-----------------|-------------|-----------|------------|----------|
| ASJ | Amami Airport | Amami | Japan | 28.4306 | 129.713 | 9 |
| CAN | Guangzhou Baiyun International Airport | Guangzhou | China | 23.3924 | 113.299 | 8 |
| CJU | Jeju International Airport | Cheju | South Korea | 33.5113 | 126.493 | 9 |
| CKG | Chongqing Jiangbei International Airport | Chongqing | China | 29.7192 | 106.642 | 8 |
| CSX | Changsha Huanghua International Airport | Changsha | China | 28.1892 | 113.22 | 8 |
| CTS | New Chitose Airport | Sapporo | Japan | 42.7752 | 141.692 | 9 |
| CTU | Chengdu Shuangliu International Airport | Chengdu | China | 30.5785 | 103.947 | 8 |
| DLC | Zhoushuizi Airport | Dalian | China | 38.9657 | 121.539 | 8 |
| FOC | Fuzhou Changle International Airport | Fuzhou | China | 25.9351 | 119.663 | 8 |
| FUK | Fukuoka Airport | Fukuoka | Japan | 33.5859 | 130.451 | 9 |
| GMP | Gimpo International Airport | Seoul | South Korea | 37.5583 | 126.791 | 9 |
| HFE | Hefei Luogang International Airport | Hefei | China | 31.78 | 117.298 | 8 |
| HGH | Hangzhou Xiaoshan International Airport | Hangzhou | China | 30.2295 | 120.434 | 8 |
| HKD | Hakodate Airport | Hakodate | Japan | 41.77 | 140.822 | 9 |
| HKG | Hong Kong International Airport | Hong Kong | Hong Kong | 22.3089 | 113.915 | 8 |
| HMA | Khanty Mansiysk Airport | Khanty-Mansiysk | Russia | 61.0285 | 69.0861 | 5 |

(continued on next page)

(continued)

| IATA code | Airport Name | City | Country | Latitude. | Longitude. | Timezone |
|-----------|---|-------------------|-------------|-----------|------------|----------|
| HND | Tokyo Haneda International Airport | Tokyo | Japan | 35.5523 | 139.78 | 9 |
| HRB | Taiping Airport | Harbin | China | 45.6234 | 126.25 | 8 |
| ICN | Incheon International Airport | Seoul | South Korea | 37.4691 | 126.451 | 9 |
| IKT | Irkutsk Airport | Irkutsk | Russia | 52.268 | 104.389 | 8 |
| ISG | New Ishigaki Airport | Ishigaki | Japan | 24.39639 | 124.245 | 9 |
| ITM | Osaka International Airport | Osaka | Japan | 34.7855 | 135.438 | 9 |
| KCZ | K??chi Ry??ma Airport | Kochi | Japan | 33.5461 | 133.669 | 9 |
| KHH | Kaohsiung International Airport | Kaohsiung | Taiwan | 22.5771 | 120.35 | 8 |
| KHV | Khabarovsk-Novoy Airport | Khabarovsk | Russia | 48.528 | 135.188 | 10 |
| KIJ | Niigata Airport | Niigata | Japan | 37.9559 | 139.121 | 9 |
| KIX | Kansai International Airport | Osaka | Japan | 34.4273 | 135.244 | 9 |
| KJA | Yemelyanovo Airport | Krasnoyarsk | Russia | 56.1729 | 92.4933 | 7 |
| KMI | Miyazaki Airport | Miyazaki | Japan | 31.8772 | 131.449 | 9 |
| KMJ | Kumamoto Airport | Kumamoto | Japan | 32.8373 | 130.855 | 9 |
| KMQ | Komatsu Airport | Kanazawa | Japan | 36.3946 | 136.407 | 9 |
| KOJ | Kagoshima Airport | Kagoshima | Japan | 31.8034 | 130.719 | 9 |
| MFM | Macau International Airport | Macau | Macau | 22.1496 | 113.592 | 8 |
| MYJ | Matsuyama Airport | Matsuyama | Japan | 33.8272 | 132.7 | 9 |
| NGB | Ningbo Lishe International Airport | Ninbo | China | 29.8267 | 121.462 | 8 |
| NGO | Chubu Centrair International Airport | Nagoya | Japan | 34.8584 | 136.805 | 9 |
| NGS | Nagasaki Airport | Nagasaki | Japan | 32.9169 | 129.914 | 9 |
| NKG | Nanjing Lukou Airport | Nanjing | China | 31.742 | 118.862 | 8 |
| NRT | Narita International Airport | Tokyo | Japan | 35.7647 | 140.386 | 9 |
| OKA | Naha Airport | Okinawa | Japan | 26.1958 | 127.646 | 9 |
| OVB | Tolmachevo Airport | Novosibirsk | Russia | 55.0126 | 82.6507 | 7 |
| PEK | Beijing Capital International Airport | Beijing | China | 40.0801 | 116.585 | 8 |
| PUS | Gimhae International Airport | Busan | South Korea | 35.1795 | 128.938 | 9 |
| PVG | Shanghai Pudong International Airport | Shanghai | China | 31.1434 | 121.805 | 8 |
| SDJ | Sendai Airport | Sendai | Japan | 38.1397 | 140.917 | 9 |
| SGC | Surgut Airport | Surgut | Russia | 61.3437 | 73.4018 | 5 |
| SHA | Shanghai Hongqiao International Airport | Shanghai | China | 31.1979 | 121.336 | 8 |
| SHE | Taoxian Airport | Shenyang | China | 41.6398 | 123.483 | 8 |
| SVX | Koltsovo Airport | Yekaterinburg | Russia | 56.7431 | 60.8027 | 5 |
| SYX | Sanya Phoenix International Airport | Sanya | China | 18.3029 | 109.412 | 8 |
| SZX | Shenzhen Bao'an International Airport | Shenzhen | China | 22.6393 | 113.811 | 8 |
| TAO | Liuting Airport | Qingdao | China | 36.2661 | 120.374 | 8 |
| TPE | Taiwan Taoyuan International Airport | Taipei | Taiwan | 25.0777 | 121.233 | 8 |
| TSA | Taipei Songshan Airport | Taipei | Taiwan | 25.0694 | 121.552 | 8 |
| TSN | Tianjin Binhai International Airport | Tianjin | China | 39.1244 | 117.346 | 8 |
| UKB | Kobe Airport | Kobe | Japan | 34.6328 | 135.224 | 9 |
| ULN | Chinggis Khaan International Airport | Ulan Bator | Mongolia | 47.8431 | 106.767 | 8 |
| UUS | Yuzhno-Sakhalinsk Airport | Yuzhno-sakhalinsk | Russia | 46.8887 | 142.718 | 11 |
| VVO | Vladivostok International Airport | Vladivostok | Russia | 43.399 | 132.148 | 10 |
| WEH | Weihai Airport | Weihai | China | 37.1871 | 122.229 | 8 |
| WUH | Wuhan Tianhe International Airport | Wuhan | China | 30.7838 | 114.208 | 8 |
| XIY | Xi'an Xianyang International Airport | Xi'an | China | 34.4471 | 108.752 | 8 |
| XMN | Xiamen Gaoqi International Airport | Xiamen | China | 24.544 | 118.128 | 8 |
| YKS | Yakutsk Airport | Yakutsk | Russia | 62.0933 | 129.771 | 9 |
| YNT | Yantai Laishan Airport | Yantai | China | 37.4017 | 121.372 | 8 |

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