Tracking the spread of COVID-19 in India via social networks in the early phase of the pandemic

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Abstract

Background: The coronavirus pandemic (COVID-19) has spread worldwide via international travel. This study traced its diffusion from the global to national level and identified a few superspreaders that played a central role in the transmission of this disease in India.

Data and methods: We used the travel history of infected patients from 30 January to 6 April 2020 as the primary data source. A total of 1386 cases were assessed, of which 373 were international and 1013 were national contacts. The networks were generated in Gephi software (version 0.9.2).

Results: The maximum numbers of connections were established from Dubai (degree 144) and the UK (degree 64). Dubai’s eigenvector centrality was the highest that made it the most influential node. The statistical metrics calculated from the data revealed that Dubai and the UK played a crucial role in spreading the disease in Indian states and were the primary sources of COVID-19 importations into India. Based on the modularity class, different clusters were shown to form across Indian states, which demonstrated the formation of a multi-layered social network structure. A significant increase in confirmed cases was reported in states like Tamil Nadu, Delhi and Andhra Pradesh during the first phase of the nationwide lockdown, which spanned from 25 March to 14 April 2020. This was primarily attributed to a gathering at the Delhi Religious Conference known as Tabligh Jamaat.

Conclusions: COVID-19 got induced into Indian states mainly due to International travels with the very first patient travelling from Wuhan, China. Subsequently, the contacts of positive cases were located, and a significant spread was identified in states like Gujarat, Rajasthan, Maharashtra, Kerala and Karnataka. The COVID-19’s spread in phase one was traced using the travelling history of the patients, and it was found that most of the transmissions were local.

Key words: COVID-19, Indian states, international travels, local transmission, superspreading event, mass gathering, Delhi religious conference

Introduction

In December 2019, China reported several patients with unusual pneumonia who had contact at the Huanan Seafood market in Wuhan to the World Health Organisation (WHO) country office.1 In January 2020, 44 patients were reported to have pneumonia with an unknown aetiology and 121 close contacts were under surveillance (www.who.int/csr/don/03-january-2020-pneumonia-of-unknown-cause-china/en/). In the following weeks, the virus spread globally. In an initial study, Bogoch et al.2 investigated the international dissemination of this disease and reported Infectious Disease Vulnerability Index (IDVI) scores for 20 destination countries receiving significant numbers of travellers from Wuhan. In this study, Dubai was among the top IDVI scorers (0.765). The outbreak was declared a Public Health Emergency of International Concern on 30 January 2020. On 11 February 2020, the WHO announced an official name for the new coronavirus disease-2019 (COVID-19).3

The first case in India was reported on 30 January 2020 from Wuhan, China. In the absence of any cure, this disease could have been fatal for a vast country such as India, affecting its 1.3 billion residents. However, as of April 2020, the COVID-19 infection rate in India was markedly lower than in other...
affected countries. This slow spread could mainly be due to 
prompt 3-week nationwide lockdown from 25 March to 14 
April 2020.5 To control the pandemic, the Indian government 
enacted a range of social distancing strategies, such as citywide 
lockdowns, screening measures at train stations and airports 
and isolation of suspected cases. A complete restriction on domestic 
and international flights was imposed by the Indian government 
during this time. Hence, the travel data available for this study 
were restricted until April 6. The exponential global spread of 
COVID-19 resulted in a 22% reduction in international travel 
followed by 57% in March 2020. This situation has put 100–120 
million tourism jobs at risk and severely affected the tourism 
sector.5

Also, it was speculated by many researchers and media that 
the widespread vaccination for tuberculosis or malaria resistance 
could have helped India remain immune to the pandemic to 
some extent, possibly slowing the rate of infection.5 As of April 
10, India's five worst-hit states were Maharashtra, Delhi, Tamil 
Nadu, Rajasthan and Telangana, which were declared hotspots 
in terms of the total number of COVID-19 infections.

In the initial phase, COVID-19's transmission was mainly due 
to international travel. Many Indians and foreigners travelled 
to Indian states from countries such as the UK, UAE, Italy, 
Wuhan, Dubai, USA, Saudi Arabia, Iran, Philippines, Thailand 
and Indonesia. Transmission of diseases that spread through 
personal contact can increase the risk of an outbreak. In a 
fully mixed population, these contacts may come from strangers 
or among acquaintances. However, most of the time in real 
problems, such fine data are not available and making such 
distinctions is not possible. Therefore, understanding how these 
diseases spread remains challenging. The explosion of devastat-
ing infections, such as severe acute respiratory syndrome (2003), 
Ebola (2014–2015), measles (2018) and Zika (2015–2016), have 
shown that the dynamics behind the spread of disease are more 
complex and limit our ability to predict and control epidemics. 
Only ∼280 people were affected by the Zika virus from Septem-
ber to November 2018, demonstrating the slow transmission of 
the virus.3,9 The largest Ebola outbreak occurred in Africa, and 
from December to January 2016, 11 310 deaths were reported.10 
In India, few significant cases were reported, but it did not 
cause a public health emergency. In 2018, measles hit regions 
in the USA.11 Although these diseases were infectious and spread 
rapidly due to human transmission, COVID-19 is the deadliest to 
date. COVID-19's reproduction number is higher than other dis-

eases.12 The WHO reported 608 800 global Covid-19 fatalities 
on 19 July 2020.

Social networks are collections of different kinds of methods, 
tools and techniques to measure relationships among various 
communities, people and organizations that can be used to 
ascertain the complexity of varying network systems. In a social 

network, contact patterns can be used to analyse disease dynam-
ics. A network can be inferred through statistical metrics such 
as degree, modularity and centrality, which are the essential 
factors that quantify a network.13 The connections are usually 
represented in the form of a graph in which individuals are 

nodes and lines connecting them are edges. Edges represent 
the strength of interactions and can be unidirected or bidirectional. 
In summary, social network analysis (SNA) provides methods to 
measure the social interactions in a population, which in turn 
can quantify the social structure of an occurrence.14 Measures 
of centrality (betweenness, eigenvector centrality and closeness) 
are typically the most directly relevant metrics to disease research 
because they measure vital aspects of an individual’s connectivity 
or importance to the overall social structure.15 Most real net-
works typically have parts in which the nodes are more highly 
connected than to the rest of the network. The sets of these 

nodes are usually called clusters, communities, cohesive groups 
or modules.16 The community detection problem is defined as the 
division of a graph into clusters or groups of nodes in which each 

includes a robust internal cohesion (the densities of edges within 
a group) and a weak external cohesion (outside the group).17 
Some well-known methods are documented in the literature, 
which enable the construction of such communities in the form 
of clusters known as modularities.18–21 In this study, the network 
was generated via Gephi software (version 0.9.2), which uses the 
Louvain method for community detection.22

The main objective of this study was to determine the social 

network behind the spread of COVID-19 in India. We demon-
strated the situation from the beginning and how the outbreak 
spread throughout Indian states via cluster formation. This work 
is an essential contribution as fewer studies are available on the 
COVID-19 transmission network as a whole.

Data and Methodology

The data utilized in this study were obtained from https://www. 
covid19india.org, which include the patient number, their state 
of residence, their travel history and the source. Gephi (version 
0.9.2) software was used for network generation and visual 
exploration. Since there was a complete restriction on domestic 
and international flights after the first lockdown in India that 
commenced on 25 March 2020, the travel data available for the 
present study were from 30 January to April 6 2020.

This software includes many essential parameters that are 
explained as follows:

Degree centrality is an important parameter that measures the 
total number of edges attached to a particular node.23 A node 
with the highest degree centrality means that the node has more 
linkage with other nodes.

There are two types of degree centrality: in-degree and out-

degree. In a directed graph, the edges that go into a node are in-
degree edges and the edges that come out of a node are out-degree 
edges. Mathematically it is expressed as:

\[ C_d = d(n_i) = X_i+ = \sum_j X_{ij}, \]  

(1)

where \( X_{ij} \) includes both in and out edges.

Closeness centrality measures how much a node is close to 
to all other nodes in a given network and can be calculated as the 
average of the shortest path length from one node to every other 
node,24 expressed as:

\[ C_c(i) = \frac{N - 1}{\sum_i d(i,j)}, \]  

(2)

where \( d(i,j) \) is the length of the shortest path between nodes \( i \) and 
\( j \) in the network, \( N \) is the number of nodes.
The Eigenvector centrality of a node is defined as the weighted sum of the centralities of all nodes that are connected to it by an edge, $A_{ij}$,

$$C_i = \frac{1}{\epsilon} \sum_{j=1}^{n} A_{ij} C_j, \quad (3)$$

where $C_j$ is the eigenvector linked to the eigenvalue $\epsilon$ of $A$.

The importance of a node in a given network is measured by its eigenvector centrality, which also gives other nodes weight. Eigenvector centrality measures how influential a node is in a given network.\textsuperscript{23}

Clustering and modularity: One of the central objectives of SNA is the identification of communities that are formed during an event. ‘Clustering’ and ‘modularity’ are the two terms that are used in this context. For example, clustering is the propensity of two nodes with a common neighbour to be neighbours of each other while modularity is the partitioning of a network into internally well-connected groups.

Community detection

The Newman–Girvan modularity is commonly used for community detection. This method detects communities by gradually removing edges from a given network\textsuperscript{26} and giving priority to the edges that are ‘between’ communities.\textsuperscript{27} Spectral clustering is another community detection method that uses the eigenvalues of a symmetric matrix.\textsuperscript{28} The modularity’s common requirement is that the connections within graph clusters should be dense. In this study, the modularity was calculated via the Louvain method.\textsuperscript{29} The Louvain method is a two-step iteration that uses a hierarchical algorithm to detect communities in a given network. The vertices are merged into a community, and it maximizes a modularity score for each community by evaluating how much more densely connected the nodes within a community are, compared to how connected they would be in a random network. This process repeats until it reaches the maximum modularity value.\textsuperscript{30}

Results

Figure 1 depicts a social network formed by contacts from 10 countries (these contacts may be Indians or foreigners) and 24 Indian states, which mainly took part in the initial disease transmission through international travel. A real network is typically comprised of nodes (units); in our case, countries were the primary nodes and represented the one-directional flow of information to Indian states. Figure 1 also shows small nodes in which patient numbers are marked; each edge represents the travel details of an infected patient from any one of the countries to Indian states. Figure 1 demonstrates how people travelled from all over the globe to different Indian states and how they formed a large number of clusters. In this network, the term ‘modularity’ is used, which measures the numbers of clusters. To better understand these clusters and how they were counted in a given network, Figure 1a shows a magnified view. It shows that Dubai has modularity Class 3, which means there are three densely placed clusters, whereas the rest of the nodes are randomly connected. Similarly, the UK has modularity Class 7, which shows it formed seven main clusters (numbers are marked in Figure 1a).

There are a few listed countries where the maximum number of people travelled to India. Figure 2 shows the number of international travellers to Indian states. The largest numbers of international contacts from different countries were established in Kerala. For example, 90 people travelled from Dubai to Kerala and 24 travelled from the UAE to Kerala. Statewise data are provided in Figure 2. It demonstrates that most of the people travelled from Dubai and the UK to Indian states. For example, people from the UK travelled to 18 different states, whereas people from Dubai travelled to 15 different states. Table 1 summarizes the metrics that quantify the number of connections from Figure 1. It shows that Dubai and the UK had 144 and 69 degrees, respectively, which indicates that the highest links were established in various states from these two countries. Table 1 shows that Dubai and the UK had the highest closeness centrality (closeness to all of the other nodes), which means these two countries were the main diffusion points as these two were connected with the maximum number of nodes. Table 1 also indicates that the UK had a higher modularity class (the number of clusters is 7) than Dubai, which means that those who travelled from the UK formed a larger number of groups across Indian states. Dubai had the highest eigenvector centrality (0.84), which means it was the most influential node. Therefore, we conclude that the UK and Dubai were the main sources of COVID-19 importations into India.

Further, it has been reported that gatherings at places of worship represent a high risk for disease transmission to potentially large numbers of people from a single case. These gatherings often involve dense mixing of many people in a confined space, sometimes over significant periods.\textsuperscript{31} For example, in March 2020, the highest number of COVID-19 cases were recorded in Malaysia, where a Muslim missionary movement in Sri Petaling was attended by >19000 people, including 1500 from India, Brunei, China, Japan, South Korea and Thailand. Overall, 1701 samples tested positive accounting for 35% of the total COVID-19 cases in Malaysia. This movement involves the Tabligh Jamaat gathering every year from around the world. Similarly, a religious congregation in Nizamuddin, Delhi, and a mass Catholic event in Northern Italy fuelled COVID-19 outbreaks in India and Italy, respectively. COVID-19 transmission linked to religious gatherings was also reported in Iran, Singapore and South Korea.\textsuperscript{32}

In India, the Delhi Religious Conference (DRC) in Delhi’s Nizamuddin area started on 13 March 2020. This event was a significant cause of the spread of COVID-19 in India. More than 3400 Islamic missionaries gathered in Nizamuddin Markaz, including missionaries from Indonesia and Malaysia. Approximately 1300 returned to their respective states during the lockdown. Afterwards, several COVID-19 cases surfaced in the states linked to this gathering. Figure 3 shows a social network that demonstrates the spread of COVID-19 across Indian states caused by this religious conference.

Table 2 summarizes the metrics that quantify the connections in Figure 3. The maximum number of infected cases by the DRC were traced in Tamil Nadu (385 degrees), Delhi (301 degrees), followed by Andhra Pradesh (138 degrees), Assam (24 degrees).
Figure 1. Network showing the International flow of people to the Indian states in the initial phase of COVID-19 spread. Nodes size is proportional to the number of connections. A zoom at higher resolution reveals that it is made of several clusters. (a) Network showing the formation of clusters using the Louvain method.

Andhra Pradesh (11 degrees). However, although the degree of connections was very high in these states due to the DRC, they formed fewer clusters outside of their communities. For example, Andhra Pradesh’s modularity class is one, Delhi’s is two and Tamil Nadu’s is three, which shows that the transmission due to the DRC remained confined to a few states.
Figure 2. Number of infected people travelled from different countries to various Indian states.

Table 1. A summary of network metrics obtained from Figure 1

| S. no | Country   | Degree | Closeness centrality | Modularity class | Eigenvector centrality |
|-------|-----------|--------|----------------------|------------------|------------------------|
| 1     | Dubai     | 144    | 0.3424               | 2                | 0.8146                 |
| 2     | UK        | 69     | 0.3156               | 7                | 0.4397                 |
| 3     | Italy     | 32     | 0.2439               | 1                | 0.2018                 |
| 4     | UAE       | 39     | 0.2532               | 2                | 0.2811                 |
| 5     | USA       | 20     | 0.2008               | 9                | 0.1441                 |
| 6     | Saudi Arabia | 19   | 0.2126               | 9                | 0.1297                 |
| 7     | Indonesia | 15     | 0.1873               | 8                | 0.0720                 |
| 8     | Iran      | 25     | 0.1907               | 5                | 0.0504                 |
| 9     | Wuhan     | 3      | 0.2162               | 0                | 0.0267                 |
| 10    | Philippines | 3    | 0.1784               | 9                | 0.0216                 |
| 11    | Thailand  | 2      | 0.1854               | 1                | 0.0144                 |

Table 3 shows that although other states had lower degrees (Gujarat, 74 degrees and Rajasthan, 32 degrees), they formed a larger number of clusters (Gujarat, 7 and Rajasthan, 8). Table 3 also demonstrates that the number of people who returned after attending the DRC in these states were less as compared to the local connections. From the data, contacts of the first positive cases were located mainly in Gujarat, Kerala, Jammu and Rajasthan. Infected persons who travelled either locally within the state or interstate came into contact with other people, which is how the virus spread. The first positive cases are marked in Figure 3.

A recent study reported that the risk of COVID-19 outbreaks in India increased because of domestic flights. The local spread of COVID-19 was also caused by railway travel, as India has 10 times more train travellers than air travellers. This might have increased the risk of the virus spreading across states.33 To better understand this local and interstate transmission, we magnified part of Figure 3 in Figure 4. When the spreader and his/her travelling history are traced, it is called the local transmission. However, in community transmission, it is not possible to detect the origin of the infected persons. Figure 4 shows the high local transmission in Gujarat (degree 74 = DRC 6 + local 59 + interstate 9). The first person who tested positive in Ramganj, a city in Rajasthan, was located and formed a cluster within the state (degree 32 = DRC 7 + local 13 + interstate 12). The connections from Rajasthan, the DRC and Karnataka demonstrated a multi-layered social network structure (including connections from local, DRC and interstate). Figure 4 also shows the connections from Maharashtra, Karnataka, Jammu Kashmir and Kerala. Maharashtra’s modularity is 6, and Karnataka’s is 8, for Jammu Kashmir it is 6 and of Kerala is 5, which means these states formed a large number of clusters, although the number of connections from the DRC were low, as shown in Table 3.

In summary, four distinct stages of COVID-19 have been identified to date.34 Stage 1 is when the disease is imported from affected countries without any local origin and it has not spread locally. Stage 2 is the phase of local transmission, which includes people with a travel history to other already affected countries.
Figure 3. A contact network including the DRC social interactions.

Table 2. A summary of network metrics obtained from Figure 3

| S. No. | States          | Degree | Modularity | Closeness centrality | Eigenvector centrality |
|--------|-----------------|--------|------------|----------------------|------------------------|
| 1      | Tamil Nadu      | 385    | 3          | 0.41                 | 0.44                   |
| 2      | Delhi           | 301    | 2          | 0.37                 | 0.34                   |
| 3      | Andhra Pradesh  | 138    | 1          | 0.33                 | 0.15                   |
| 4      | Uttar Pradesh   | 11     | 5          | 0.30                 | 0.01                   |
| 5      | Assam           | 24     | 4          | 0.31                 | 0.02                   |

Table 3. A summary of network metrics obtained from Figure 4

| S. No. | States         | DRC | Local | Inter-state | Degree (DRC + Local + State) | Modularity | Closeness centrality | Eigenvector centrality |
|--------|----------------|-----|-------|-------------|-------------------------------|------------|----------------------|------------------------|
| 1      | Gujarat        | 6   | 59    | 9           | 74                            | 7          | 0.44                 | 1                      |
| 2      | Rajasthan      | 7   | 13    | 12          | 32                            | 8          | 0.34                 | 0.18                   |
| 3      | Karnataka      | 13  | 3     | 8           | 24                            | 8          | 0.24                 | 0.10                   |
| 4      | Maharashtra    | 7   | 11    | 0           | 18                            | 6          | 0.24                 | 0.06                   |
| 5      | Kerala         | 0   | 5     | 0           | 5                             | 5          | 0.85                 | 0.009                  |
| 6      | Jammu & Kashmir| 0   | 6     | 0           | 6                             | 6          | 0.87                 | 0.01                   |
Stage 3 is the phase of community transmission where the source of the disease is untraceable and the infected individual cannot be isolated. Once the population enters Stage 3, individuals contract infections randomly and it becomes difficult to track the disease.

Hence, we concluded that COVID-19’s transmission in India remained at the local level (Stage 2) as of 6 April 2020. In addition to the outburst due to the DRC, it did not develop into community transmission (Stage 3) because of the timely isolation of infected patients in Delhi.

**Discussion and Conclusions**

Over the past few decades, world connectivity via air travel has increased markedly. Increased air travel has facilitated the spread of infectious diseases geographically. Travelling from high infection rate origins to destinations where the infection rate is lower has a huge impact on disease transmission. In countries with poor testing, poor contact tracing and fragile health care facilities will most likely lead to increased global transmission. In this study, we are only considering cases imported into Indian states from domestic and international travel. The medical infrastructure has collapsed even in the developed countries like the USA and Italy due to the surge in COVID-19 cases.

Social media also plays a major role in spreading knowledge and awareness about health issues. However, it is often misleading and spreads ‘fake news’, especially during crises. In the case of COVID-19, even before cases were detected, social media panic hit Indian society. As a result, people started to buy N95, surgical masks and sanitizers in abundance, which led to shortages. A shortage of masks was reported among frontline health care workers who needed them the most. Unfortunately, the leading blogs and newspapers also spread fake news. These observations demonstrate that the Indian government needs to more effectively regulate social media.

In this analysis, the metrics of social contacts revealed that in the initial transmission phase, many local connections were established mainly from countries such as Dubai and the UK. The statistical metrics indicate that Dubai had 144 degrees, and its eigenvector centrality was the highest. However, seven modularity classes (number of clusters) formed from the UK. Therefore, we can conclude that the UK played a central role in transmitting COVID-19 in India. Dubai had the highest eigenvector centrality, which means it was the most influential node. The modularity class of states such as Tamil Nadu, Delhi and Andhra Pradesh and those who attended the DRC was low. Hence, it is likely that infected cases from these states played less of a role in spreading the disease outside their communities. Whereas states like Gujarat, Rajasthan, Maharashtra, Kerala, Jammu Kashmir and Karnataka played a significant role in the local transmission, and some of them caused interstate transfer too.

The UK and Dubai were the primary sources of COVID-19’s importation into India. Afterwards, domestic and international flights were completely restricted; hence, only travel data from 30 January to April 6 were available for this study. A countrywide lockdown was imposed by the Indian government during the
first transmission phase from 25 March to 14 April 2020. Since those who attended the DRC were isolated during this period, the transmission of disease did not reach up to the community level.

An increase in the infected cases has been witnessed around 31 May 2020, when the country lockdown was lifted. With more contacts between the populations, a surge in COVID-19 cases was seen. As of July 30, the number of cases has reached 16 39 350, which brought India among top hit countries. More research needs to be carried out to understand the spread of infectious diseases in countries with large populations. A better understanding will help countries prepare for such occurrences.

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**Author Contributions**

S.A. designed the idea of the study and finalized the manuscript; S.D. collected data, generated figures and wrote the initial draft. Both the authors contributed equally in analyzing the results.

**Conflict of Interest**

Authors have no conflict of interest.

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