Quantitative Framework for Establishing Low-Risk Inter-District Travel Corridors During COVID-19

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Abstract
Aspirations to slow down the spread of novel Coronavirus (COVID-19) resulted in unprecedented restrictions on personal and work-related travels in various nations across the globe in 2020. As a consequence, economic activities within and across the countries were almost halted. As restrictions loosen and cities start to resume public and private transport to revamp the economy, it becomes critical to assess the commuters’ travel-related risk in light of the ongoing pandemic. The paper develops a generalizable quantitative framework to evaluate the commute-related risk arising from inter-district and intra-district travel by combining nonparametric data envelopment analysis for vulnerability assessment with transportation network analysis. It demonstrates the application of the proposed model for establishing travel corridors within and across Gujarat and Maharashtra, two Indian states that have reported many COVID-19 cases since early April 2020. The findings suggest that establishing travel corridors between a pair of districts solely based on the health vulnerability indices of the origin and destination discards the en-route travel risks from the prevalent pandemic, underestimating the threat. For example, while the resultant of social and health vulnerabilities of Narmada and Vadodara districts is relatively moderate, the en-route travel risk exacerbates the overall travel risk of travel between them. The study provides a quantitative framework to identify the alternate path with the least risk and hence establish low-risk travel corridors within and across states while accounting for social and health vulnerabilities in addition to transit-time related risks.

Keywords
planning and analysis, transportation planning analysis and application, decision making, scenario planning, public transportation, planning and development, network

Since the first reported case of novel Coronavirus (COVID-19) in Wuhan, China, in mid-December 2019, 215 countries and territories have reported around 43 million confirmed cases with more than 1.1 million fatalities as of October 25, 2020 (¹, ²). Two low-income countries that have suffered the major impact of the spread measured by number of reported cases of COVID-19 are Brazil and India (³). While Brazil has reported nearly 5.4 million COVID-19 cases with more than 150,000 deaths, India has reported 7.86 million confirmed cases with more than 119,000 deaths, as of October 25, 2020 (⁴).

For the first time in history, on March 24, 2020, a nationwide lockdown was imposed in India to contain the spread of COVID-19, limiting the movement of the 1.3 billion population (⁴, ⁵). Policymakers worldwide have implemented massive travel restrictions and quarantining policies to mitigate the outbreak and reduce the stress on already reeling healthcare and emergency facilities, especially in developing countries and vulnerable communities (⁵–⁸). While the outbreak of deadly COVID-19 took a toll on individuals’ lives and wellbeing (⁹), nationwide lockdowns severely affected economic activity within and across the country. Manufacturing, supply chain, and

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logistical activities, as well as retail activities have been severely crippled during the strict lockdown (10–12). Subsequently, to bring the affected economy back on track, in India, intra-state travel was permitted in a phased manner outside containment zones from the beginning of June 2020. Domestic flights have been allowed subject to compliance with the government’s guidelines ensuring the passengers’ safe travel amidst the pandemic. Unrestricted vehicular movement within and across the states was permitted beginning late July–early August (13).

With unrestricted travel permitted, regions that reported fewer cases during the initial phase of disease spread started reporting a significant number of cases attributed to the increased population mobility from other regions (14). While control measures such as symptoms-based screening protocols were enacted at various airports and checkpoints, these were not sufficient to contain the pandemic spread as the majority of such cases arrive during an incubation period that is usually asymptomatic (15). Moreover, symptom-based surveillance protocols are challenging to enforce for road and rail transportation given multiple entry and exit points on the travel routes (16).

The travel corridor concept has emerged to address the tradeoffs between the attempts to control the disease spread by restricting human mobility and attempts to revive the economy by establishing travel routes across the regions (17). Travel corridors are regional pacts between states that lower the travel barriers across the regions (18). While establishing travel corridors to restart commercial passenger services, trade, and economic activities is mutually beneficial (19), identifying travel corridors among regions solely based on case prevalence could result in underestimation of the risk.

This paper argues that identifying the interregional travel corridors needs to account for social and health vulnerabilities of the regions being linked and account for the possibilities of en-route exposure to the contagious disease during transit. The concept of establishing a travel corridor is based on the principle that the regions being connected have comparable demographic and socio-economic conditions. Moreover, the chances of importing new caseload should be minimal to avoid further stresses on healthcare systems and emergency services. It is thus imperative to assess the social and health vulnerability indices and overall infection rates in the regions concerned. While assessing social vulnerability to COVID-19 has gained significant attention at the regional and county scale (20–22), the possibilities of en-route risk of exposure to infectious disease are seldom analyzed. Analysis of en-route exposure and risk becomes particularly crucial in the context of developing nations, including India, where road and rail constitute the most common mode of public transportation for intra-state and inter-state travel (23). In mass public transit, adherence to physical distancing is lacking in densely populated regions. While there is emerging evidence that the use of facemasks in closed settings can significantly reduce contagion risk (24), enforcing compliance is challenging. There is thus a growing concern that public transit can be viewed as unhealthy in the post-pandemic world. This belief, in turn, may translate into behavioral changes of passengers and alter their choices from public mode to privately owned modes (25). In long-distance travel via road, drivers often develop motorist fatigue and use roadside parking or rest areas to alleviate their tiredness (26). Also, long-haul public transportation facilities have multiple en-route stops both for obligatory stops and to enable boarding and deboarding of the passengers (27). Thus, there is a risk of en-route exposure to highly prevalent and contagious diseases, including COVID-19, from both public and private modes of transportation.

In a first-of-its-kind study, the authors develop a generalizable quantitative framework to identify low-risk inter-district travel corridors during the prevalence of COVID-19. The commute-related risk arising from inter-district and intra-district travels is evaluated by combining nonparametric data envelopment analysis (28–31) for assessment of social and health vulnerability with the underlying transportation networks (32, 33). The application of the proposed model is demonstrated for identifying travel corridors within and across Gujarat and Maharashtra, the two Indian states that have reported a significant share of COVID-19 cases since early April 2020. The proposed approach’s effectiveness is further studied by constructing the n-walk matrix between a pair of districts to identify all possible rerouting options and evaluating the least vulnerable route between the travel corridor’s origin and destination nodes. Note that the clinical characteristics associated with the COVID-19 (e.g., transmissibility, recovery, and mortality rates), varying travel speeds on various road segments within the states, congestion during peak-traffic hours, and administrative restrictions to travel through containment zones can affect the disease trajectory and thus the en-route risk of exposure in real time. Such effects are not included within the scope of this research.

Methods

Data

The neighboring states of Gujarat and Maharashtra, India, were chosen as the study area to demonstrate the application of the proposed framework. The choice of Gujarat and Maharashtra as the study regions was guided by the availability of credible data required for assessment of socio-economic and health vulnerability
Located on the western coast of India, Gujarat and Maharashtra are two of the fastest-growing and leading industrialized states in India (35). With a combined population of 170.7 million, Maharashtra and Gujarat are the second and ninth most populous states in India and are home to densely populated urban centers, including Mumbai and Ahmedabad (36). Given that the high population densities, availability of opportunities, and continued financial activities increased the risk of transmission in both states, Maharashtra has reported the highest number of cumulative cases in India as of October 25, 2020, whereas Gujarat reported the highest mortality rates in the initial phases of lockdown (Figure 1) (37, 38). Maharashtra and Gujarat rank among the top states measured by manufacturing emergence and contribute nearly 50% to India’s total exports (35). Given the geographical proximity and high volumes of inter- and intra-state transit volume, this study analyzed inter-district travel in the 59 districts of the two states.

The extent of adverse impacts from a disaster is influenced by the magnitude and intensity of hazards, as well as the degree of vulnerability of the exposed society (39). Vulnerability captures the susceptibility, exposure, coping capacity, and adaptive capacity of the community involved in a natural disaster. The concept of vulnerability has been used globally to analyze the impact of hazardous environmental and climate changes for assessing the disaster risk as well as to minimize vulnerability by improving disaster management strategies (40). Quantitative assessments of vulnerability typically use various physical, social, economic, health, and environmental factors. This study focuses on quantification of social and health vulnerability. To identify regions of similar vulnerability, between which potential travel corridors can be established, social and health vulnerability indices are computed using various indicators from 2011 census data (36). Social vulnerability is calculated based on the characteristics and ability of the community to govern under external stressors (disaster). Specifically, the densities of total population, number of households, infant population, non-working population, gender ratio, illiterate population, rural population, persons with disabilities, and households without electricity aggregated at district scales were used as indicators for computing social vulnerability (36, 41). Note that economic growth and immigration of workers since 2011 may have significantly altered the values of these indicators. Here the same relative growth across all the districts is assumed, in the absence of recent census data; new census data is scheduled to be released in the year 2021 (42). Further, to calculate the indicators of health vulnerabilities, the authors used data on dedicated COVID-19 hospitals,
sub-centers, primary healthcare centers (PHCs), community healthcare centers, and sub-divisional hospitals sourced from GRAM (43), and district level COVID-19 patient counts (both confirmed cases and deceased patients) obtained from Covid19India (44). These parameters provide an understanding of the stress of epidemic spread in the region (in this case COVID-19 patients) and the capacity of the region to tackle the spread. It is necessary to consider both social and health vulnerability, as the former gives information on those regions that could have a higher potential vulnerability while the latter can give information on the region’s vulnerability to external stress (in this case, COVID-19 spread). To construct the transportation network, Google Maps was used to extract the major inter-district roads.

Vulnerability Analysis

It is imperative to categorize the regions that share similar demographics and underlying factors governing social and health vulnerabilities to identify the potential travel corridors. In the proposed framework, the social and health vulnerability indices were calculated for each district (nodes) and the health vulnerability index for the road segments (edges) connecting the centroids of neighboring districts. While the associated node vulnerability aids in clustering similar districts together, edge vulnerability determines the en-route risk associated with the prevalent contagious disease. Finally, the vulnerability indices thus obtained were integrated with the transportation network to assess the travel risk between a pair of origin and destination districts, which, in turn, helps to identify the possible travel corridors with the least transit risk (Figure 2).

Variable Selection and Normalization. The three approaches typically used by researchers to select the indicator variables to calculate vulnerability indices are: the deductive approach (45), the inductive method (40), and the hierarchical approach (30, 46). The deductive approach is based on the theoretical understanding of the relationship between parameters. It involves the selection of parameters based on past literature or based on the expert’s review (45). The hierarchical approach is also based on theoretical understanding, but here the participatory or expert’s opinion is used to select and weigh the parameter. The prime example of this type of approach is the analytic hierarchy process. On the contrary, in the inductive method, parameters are selected based on statistical techniques, including principal component analysis, to de-correlate and reduce the dimensionality among the candidate variables for vulnerability assessment. In the present study, the parameters for social vulnerability mapping were selected based on the inductive approach, as identified by Vittal et al. (40). For the social and health parameters outlined in the Data section, the density was calculated for each parameter by dividing the area of the respective district, and then “min-max” rescaling was used to standardize the data (29, 40) Mathematically, the transformation is shown in Equation 1:

$$ V_i = \frac{Y_i - Y_{\text{min}}}{Y_{\text{max}} - Y_{\text{min}}} $$

where

- $V_i$ = transformed value of parameters used to assess vulnerability, scaled between 0 and 1
- $Y_{\text{max}}$ = maximum value of the social parameter
- $Y_{\text{min}}$ = minimum value of the social parameter.

Data Envelopment Analysis. Data envelopment analysis (DEA) is a nonparametric mathematical linear programming-based optimization technique originally introduced in Charnes et al. (28). DEA calculates the technical efficiency frontier (equivalent to social and
health vulnerability) of decision making units (DMUs) (represented by the 59 districts in this study). DEA optimizes each observation to compute the discrete piecewise frontier estimated from the parieto-efficient DMUs. The number of DMUs should be higher than the number of inputs and outputs, and the variables must have a low correlation while conducting the DEA; otherwise, the computing capability of the DEA model to calculate the efficiency is reduced. The technique of DEA is widely used for efficiency measurements in disparate fields, including education (47), banking (48), transportation (49), and the health sector (50). The present study used the dual form of the Charnes Cooper Rhodes model, which is built on the assumption of constant return to scale activity (28), as described below (Equations 2–5):

$$\text{Min } \theta_k - \epsilon \left( \sum_{i=1}^{s} S_i^+ + \sum_{i=1}^{m} S_i^- \right)$$  \hspace{1cm} (2)

subject to:

$$\sum_{i=1}^{n} \lambda_i y_{ij} - S_r^+ - y_{rk} \text{ where } r = 1, 2, \ldots, s$$  \hspace{1cm} (3)

$$\theta_k - x_{ik} \sum_{i=1}^{n} \lambda_i x_{ij} - S_i^- = 0 \text{ where } r = 1, 2, 3, \ldots, m$$  \hspace{1cm} (4)

$$\lambda_j, S_i^-, S_r^+, \epsilon \geq 0$$  \hspace{1cm} (5)

where

- $k =$ DMU, or district identity
- $\theta_k =$ technical efficiency
- $m =$ number of inputs
- $n =$ number of DMUs
- $s =$ number of outputs
- $x_{ik} =$ observed magnitude of parameter $i$ for district $k$
- $\lambda_j =$ weight assigned to parameter $j$
- $S_i^-, S_r^+ =$ slack variables
- $y_{ij} =$ observed magnitude of input $i$ for entity $j$

For social vulnerability ($SV$), $y_{ij} = 1$ for all $n = 59$ districts in the absence of any prior data (40). Social vulnerability was defined as the state of a system before the occurrence of a hazard; a dummy output that has unity value was considered for all DMUs (31, 40, 41). For health vulnerability ($HV$), $s = 2$ where $y_{ij}$ and $y_{ik}$ are the standardized values of confirmed and deceased cases, respectively. The total vulnerability ($TV$) of districts is calculated by taking the geometric mean of social and health vulnerabilities (51) (Equation 6):

$$TV = \sqrt{(SV \times HV)}$$  \hspace{1cm} (6)

**Transportation Network Analysis**

To calculate the en-route aggregated risk arising from inter-district travel, inter-district road network data were analyzed. The centroids of neighboring districts were connected using the shortest path, computed using Google Maps. The resulting network thus obtained has district centroids as nodes, and the shortest routes connecting these nodes represent the links. In risk assessment studies, hazard (probability of event), vulnerability, and exposure are in a multiplicative linear relationship to calculate the risk (52–57). In this study, the vulnerability parameter is represented by the health vulnerability of the district (during COVID-19), and the exposure parameter is represented using the proportion of travel time spent in the districts.

Finally, the en-route travel risk ($TR$) to each edge connecting the neighboring districts was calculated using Equation 7. Travel risk depends on the amount of health vulnerability in proportion to the travel time spent in the district. It is also normalized with respect to the maximum available travel time between the neighboring districts to scale the travel risk between zero and one. The total travel risk of travel from origin to destination through multiple intermediate districts on the route is calculated by using Equation 8. A detailed process flowchart, along with data used in the present study, is shown in Figure 3. Here only the inter-district travel between Maharashtra and Gujarat is considered. The effect of travel between other states and international travel except for the two states considered was left out because of the restrictions on such travel at the time of the study.

$$TR_{AB} = \frac{(T_{Ai} \times HV_A) + (T_{Bi} \times HV_B)}{T_{max}}$$  \hspace{1cm} (7)

where

- $T_{Ai} =$ time taken from centroid of district A to the boundary of district B
- $HV_A =$ health vulnerability of district A
- $T_{Bi} =$ time taken from centroid of district B to the boundary of district A
- $HV_B =$ health vulnerability of district B
- $T_{AB} =$ total travel time between centroid of districts A and B
- $T_{max} =$ maximum travel time between the centroid of the available neighboring pairs of districts

$$TTR = \sum_{p=1}^{n} \left( \frac{T_{ip} \times HV_p + T_{ip}(p + 1) \times HV_{p + 1}}{T_{max}} \right)$$  \hspace{1cm} (8)

where

- $p =$ origin district of travel
- $n =$ total number of districts crossing selected route
Results and Discussions

Table 1 provides the summary statistics of parameters used for assessing social and health vulnerabilities and travel risk (in units of quantity per square kilometer). The densities of total population, number of households, infant population (aged 0–6 years), non-working population, gender ratio, illiterate population, rural population, persons with disabilities, and households without electricity aggregated at district scales were considered as the parameters for calculation of social vulnerability. The counts of dedicated COVID-19 hospitals, sub-centers, PHCs, community healthcare centers, confirmed COVID-19 patients, deceased COVID-19 patients, and sub-divisional hospitals were used as parameters for calculation of health vulnerability. These parameters are listed in Table 1. The statistics in Table 1 suggest that both the overall population density and the working population density in Maharashtra were significantly higher than in Gujarat. However, the mean illiterate population and non-working population density in Maharashtra was also significantly higher than in Gujarat. A higher population, along with high illiteracy, may have placed Maharashtra in the category of higher social vulnerability in comparison with Gujarat. In the case of health infrastructure, the mean density of dedicated COVID-19 hospitals and PHCs was

\[ TTR = \text{total travel risk for the selected route} \]

Other terms have similar meanings to those presented for Equation 7.

Figure 3. Flowchart outlining the datasets and processes involved in health and social vulnerability assessment to identify low-risk inter-district travel corridors among 59 districts of Gujarat and Maharashtra.
higher in Maharashtra than in Gujarat. These COVID-19 hospitals, including the medical colleges and district hospitals, generally located in the city centers of each district (https://covidindia.org), are the important centers currently working for COVID-19 treatment in India. PHCs are the centers for collecting test samples for COVID-19 tests. While these facts would suggest that Maharashtra was in a better position to manage the disease reactively, the mean of confirmed and deceased patient counts (see Table 1) in Maharashtra was approximately 10 times higher than in Gujarat, indicating the prevalent rampant spread of COVID-19. This indicates a vulnerable situation for Maharashtra.

Further, these observations were examined in the DEA to identify the more vulnerable districts in both states. Note that, officially, there are 36 districts in Maharashtra. However, based on the data availability, the data for two districts were combined with adjacent districts to observe a total of 34 districts in Table 1. Greater Mumbai (or Bombay) represents the Mumbai City district and Mumbai Suburban district, which share an integrated transportation system and administration. Similarly, the Thane district in this study represents the Palghar district and Thane district together. The Palghar district came into existence in 2014; before that, it was part of the Thane district.

The DEA yields the efficiency scores of DMUs, which, in this study, are the vulnerability scores of the districts considered. Those scores were between zero and one, representing the relative vulnerability (risk) of the corresponding district. The vulnerability scores are available for social, health, and a combination of social and health factors. Each factor is classified into five levels representing very high, high, moderate, low, and very low vulnerability. See Figure 4 for districts with different levels of vulnerability based on social and health factors, and combinations of social and health factors. The Jenks Natural Breaks Classification technique available in ArcMap® is used to classify the districts. This technique determines the best grouping of vulnerability values based on the user-defined number of classes. It iteratively compares the sums of the squared difference between observed values within each class and class means. The best classification identifies breaks in the ordered distribution of values that minimizes the within-class sum of squared differences.

As discussed above, the observations from Figure 4a suggests that Maharashtra certainly has higher social vulnerability compared with Gujarat. Among the 59 districts in Maharashtra and Gujarat, 25% of districts have high to very high social vulnerability index, of which only one district is in Gujarat. Further, the social vulnerability assessment in Figure 4a indicates that the south-west region of Maharashtra has high to very high social vulnerability compared with other districts. Interestingly, the capital of Maharashtra, Mumbai, seems highly vulnerable. Despite being the financial center of India, Mumbai is also home to Asia’s largest densely populated slum area, called Dharavi. The people in Dharavi are under-privileged with a very low literacy rate. Possibly,
for this reason, the social vulnerability of Mumbai is very high. Apart from Mumbai, the DEA indicated that districts with very high vulnerability have high illiterate population, non-working population, and infant population. Further, the districts with very low to low vulnerability have higher working female populations. In Gujarat, the Kachchh district is identified as the region of highest social vulnerability because of its high illiteracy rate, larger rural population with marginal workers, and higher density of households without electricity. Other districts in Gujarat have very low to moderate social vulnerability.

While a well-connected transportation network is conducive to the economic prosperity of a region, it can open the gateway for entry of new infected cases during the prevalence of a pandemic. However, the health infrastructure could be insufficient to deal with such a pandemic. In the context of health vulnerability for Gujarat: Patan, Porbandar, Vadodara, and Narmada districts show very high vulnerability as the health infrastructure available to tackle the COVID-19 is very low compared with the patient cases in these districts. Ahmedabad and Surat, being the financial hubs of Gujarat, show high vulnerability because of the high numbers of COVID-19 patient cases (Figure 4b). For Maharashtra, Mumbai has one of the busiest single-runway international airports in the world and is well connected by roads and railways with other parts of the country. Any individual with COVID-19 infection entering Mumbai can contribute to the rapid spread of the disease in Mumbai as well as in the nearby districts of Maharashtra. Districts with good connectivity with Mumbai have reported a higher number of cases compared with other districts. Mumbai is located on the west coast of Maharashtra. Consequently, the western region of Maharashtra state, as shown in Figure 4b, has a high patient count and more vulnerable districts compared with its eastern region and Gujarat state. It includes prominent districts such as Thane, Pune, Nasik, Aurangabad, and Sangali. In the eastern part of Maharashtra, the Nagpur district showed high health vulnerability. Note that it is well connected with Mumbai and other prominent cities in India through various transport modes (air, rail, and road). Being at the center of India, Nagpur airport is strategically developing into a multi-modal international cargo hub for goods transportation. Since it is not fully operational to date, the neighboring districts relatively have a lower vulnerability. Overall, Figure 4c suggests that the total vulnerability was very high in Maharashtra compared with Gujarat. This seems logically correct since the number of COVID-19 patients in Maharashtra is almost 10 times that of Gujarat.

As mentioned above, each district is represented as a node at the centroid for the network analysis. The

Figure 4. Data envelopment analysis-based assessment of: (a) social vulnerability, (b) health vulnerability, and (c) total vulnerability (geometric mean of social and health vulnerability). Note: Pie-chart in the inset of each figure shows the percentage of districts belonging to each class.
shortest route (edge) between neighboring district centroids was obtained from Google Maps. The total vulnerability is assigned to the centroid/node of the district. However, for the links, a weighted health vulnerability is assigned to identify the risk of routes. It is based on the hypothesis that individuals living/staying in a district would be vulnerable to the surrounding social characteristics and their health vulnerability will be a function of COVID-19 cases and health infrastructures of the district. However, while traveling, they are only vulnerable to the en-route COVID-19 risk. The weights of such links are calculated using Equation 7. The nodes and links for Maharashtra and Gujarat districts are color-coded as per the spectrum-full bright classification available in ArcGIS (Figure 5a). The respective color code for nodes represents the district vulnerability, while links provide the neighboring district travel vulnerability. Figure 5a illustrates the weighted risk on the links of neighboring districts. Figure 5b shows a $14 \times 14$ en-route travel risk matrix sampled from the $59 \times 59$ matrix for better readability. Based on the network, associated matrix, and calculations illustrated in Figure 6, a user can decide whether to travel on a particular link and choose a comparatively low-risk route for traveling from origin to neighboring destination district. The weighted travel network thus obtained can help us understand the total travel risk. For example, Vadodara and Narmada, two districts of Gujarat, have low and high resultant vulnerabilities, respectively. However, the en-route travel risk is very high, because of the greater health vulnerability of the Vadodara district, which in turn can be explained by many reported cases and larger centroid-to-boundary distance that travelers experience in Vadodara than in Narmada.

Overall, using the en-route travel risk path, a user can assess the travel risk, both quantitatively and qualitatively, along the alternate origin–destination paths while accounting for the availability of health infrastructure conditions at the destination district.

Note that, in a real-world network between a pair of districts, including the one developed here, multiple routes of varying network lengths are possible. This research demonstrates a method to quantify risk along one of the representative paths, which in most cases is the shortest path. However, to determine the travel risks exhaustively, one has to consider the many combinations that can be guided by the n-walk matrix (Figure 7). It is thus critical to know how many n-walk routes exist between an origin–destination pair. To address this, the adjacency matrix $A_{ij}$ of the network is calculated, as shown in Figure 7a. Element $a_{ij}$ of the matrix $A_{ij}$ would be equal to one if the district $j$ is connected to district $i$, and zero otherwise (Figure 7a). The n-th power of $A_{ij}$ thus obtained would yield the total number of n-length walks between a pair of districts along which the travel risk calculations would be performed to identify the path with least en-route risk (Figure 7b) using the procedures outlined in Figure 6.

Conclusion

Lockdowns to curb the spread of COVID-19 brought transportation systems to a standstill, severely affecting economic, trade, and tourism activities worldwide. As nations and states plan to open up their borders despite the prevalent pandemic, there is a greater need to make informed decisions to keep the virus spread in check. This paper developed a quantitative framework based on social vulnerability and health vulnerability to identify potential low-risk travel corridors for inter-district travel. The risk of contagion depends on the disease prevalence in a community at a given time. Therefore, in addition to assessing the associated risks at origins and destinations, travel corridors should account for en-route travel risks to identify the safest, shortest routes and detours. The application of the proposed model is demonstrated for establishing travel bubbles within and across Gujarat and Maharashtra in India, however, the proposed plan can be applied to other regions for domestic and international travel planning with appropriate contextualization.

Transportation organizations and planning agencies in India and elsewhere can use this framework by scaling up the current framework to establish the whole nation’s low-risk inter-district travel corridors. Transportation organizations could control the travel demand along low-risk travel corridors that can restrict unnecessary travel demand to contain the spread of the infection within a group of districts. Thus, this study can inform decision makers to reasonably develop several travel bubbles within a group of districts which will help in reviving the economy of the region as well as containing the spread of infection within a defined bubble. Key challenges that need to be addressed to scale up and operationalize the proposed strategy include the availability of homogeneous socioeconomic vulnerability data at local scales and continuous data streams associated with regions’ real-time contagion spread.

There are specific caveats related to the demonstration of the proposed framework. While this study assumed uniform travel speed throughout the network, real-time mobility patterns accounting for more accurate descriptions of congestion, delays, and stops could alter the en-route risk factors dynamically. The application of this framework can be extended to rail transportation with appropriate contextualization, as demonstrated for the road transportation in this study. For air transportation,
the origin and destination vulnerabilities can be used to calculate the travel risk as intermediate stopping options will not be applicable. Further, this study used the socio-economic indicators from the 2011 census, given the decadal frequency of census surveys in India. However, the two states studied have witnessed substantial worker immigration from various regions in the past decade (59). Accounting for such changes could change the social vulnerability classification of highly industrialized districts. Specific clinical interventions including vaccines or

Figure 5. (a) Inter-district risk network, where nodes represent the total vulnerability of district and road network (links) depicting the risk associated with inter-district travel. (b) En-route travel risk matrix for 14 districts.

Note: TTR is calculated by adding the cells above (or below) the diagonal of the en-route travel risk (TR) matrix and, in this example, it indicates option (b) as the safest route.
Figure 6. Illustration of en-route total travel risk (TTR) between origin (Surat) and destination (Thane): (a) route via Dhule–Nashik results in TTR of 0.75. Similarly, (b) the route via Navsari–Valsad results in TTR of 0.29, and (c) the route via The Dangs–Nashik results in TTR of 0.51.

Note: TTR is calculated by adding the cells above (or below) the diagonal of the en-route travel risk (TR) matrix and, in this example, it indicates option (b) as the safest route.
enforcing/lifting lockdown measures lie outside the scope of public transportation managers, but measures discussed in this work can help them in risk-informed decision making, to issue travel advisories and establish travel corridors that pose the least risk to the public.

**Author Contributions**

The authors confirm contribution to the paper as follows: study conception and design: U. Bhatia, A. Maji; data collection: R. Dave, T. Choudhari; analysis and interpretation of results: R. Dave, T. Choudhari, U. Bhatia, A. Maji; draft manuscript preparation: R. Dave, T. Choudhari, U. Bhatia, A. Maji; R. Dave and T. Choudhari. All authors reviewed the results and approved the final version of the manuscript.

**Declaration of Conflicting Interests**

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

**Funding**

The author(s) received no financial support for the research, authorship, and/or publication of this article.

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**Figure 7.** Adjacency matrix, $A_{ij}$, of the network: (a) indicates the presence of one-length walk and (b) indicates the presence of three-length walks. Note: Diagonals of the matrices are made zero to avoid self-loops.
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