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Introduction

The novel coronavirus 2019 (COVID-19) pandemic has had a substantial impact around the world. According to the latest data from the World Health Organization (WHO), as of December 22, 2020, more than 77.33 million confirmed cases and 1.70 million deaths have been reported worldwide. Transportation systems play an important role in controlling the spread of the virus and supporting the resumption of production during the COVID-19 pandemic. At the early stage of the pandemic, many countries or cities issued “stay-at-home” orders to prevent and control the virus spread. For example, in Wuhan, the...
government issued outbound travel bans at a very early stage to prevent the virus from spreading. Studies have shown that the Wuhan travel ban and national emergency response slowed the expansion of the pandemic and ultimately limited the scale of COVID-19 in China. It is estimated that the closure of Wuhan effectively delayed the spread of the pandemic to other cities by 2.91 days (Tian et al., 2020). Meanwhile, transportation systems also contribute to the reopening of the economy: after the pandemic was controlled, the road transportation system served the role of supporting the resumption of work and production. In America, the federal government relaxed its “stay-at-home” orders and social distancing measures in mid-May. Many European countries have gradually relaxed some of their travel restrictions since May as well. Travel behaviors and traffic patterns have changed in the post COVID-19 period. For example, an SP survey on the commuting behavior of residents in Shanghai showed that 41.38% of the 378 respondents turned to telecommuting and 82.31% of the users of public transport have turned to private transport modes during the work resumption period. Some research has also shown that there is a strong interaction between the pandemic and travel behaviors (Huang et al., 2020; Neuburger and Egger, 2020; Oum and Wang, 2020).

To better manage and control non-recurrent traffic conditions during and after the COVID-19 pandemic, it is important to understand the empirical traffic congestion patterns. Previous studies have focused on the evacuation congestion patterns on roadways during natural disasters or adverse weather conditions, such as hurricanes, heavy rain storms etc. (Wolshon and McArdle, 2009; Li et al., 2015). However, since a pandemic is a very rare event, there are very few empirical studies on the traffic congestion patterns that occur during and after a pandemic. There are significant differences between natural disasters and pandemics. The impact duration of natural disasters is relatively short—usually a few weeks or months—while the impact duration of pandemics can extend for several months, or even years. In addition, the traffic demands or requirements during natural disasters versus pandemics are significantly different. For natural disasters, the major concern is to evacuate people from vulnerable areas in a short time period. In contrast, during and after a pandemic, the traffic requirements are more complicated and differ across time periods. During the outbreak of a pandemic, it is important to control the virus spread by suspending transportation systems. Further, after the outbreak of a pandemic, residents’ travel behavior will change due to various factors (Arimura et al., 2020; de Haas et al., 2020; Fatmi, 2020). With the unprecedented situation of a pandemic, and the simultaneous influence of several factors, the patterns of traffic condition variation are complex and difficult to predict.

In this study, we investigate the spatio-temporal variation of roadway traffic congestion in Shanghai during and after the COVID-19 pandemic. Based on the average speed data of Traffic Analysis Zones (TAZs) in the first quarter of 2020 provided by Baidu Maps, we use the Singular Value Decomposition algorithm to extract the features of the road transportation system affected by complex factors, and we identify three main spatio-temporal change patterns. The results provide decision-making support for traffic management and control in other metropolitan areas during the COVID-19 pandemic and in the post-pandemic resumption periods.

The remainder of this paper is organized as follows. Section 2 provides a brief overview of the research related to this study. In Section 3, the study area, dataset and research methodology are described. In Section 4, three major factors are identified, and the resulting spatio-temporal variation characteristics are analyzed. Finally, conclusions and directions for future study are presented in Section 5.

**Literature review**

Previous studies related to non-recurrent traffic patterns has mainly focused on natural disasters and adverse weather conditions, including empirical analysis of travel behaviors and traffic flows, as well as evacuation modeling and simulation. Wolshon and McArdle (2009) analyzed the empirical evacuation traffic patterns in southeastern Louisiana based on real data collected during Hurricane Katrina. Chung (2012) evaluated the impact of accumulated unit rainfall and accumulated unit snowfall on non-recurrent traffic congestion per unit distance. Li et al. (2013) investigated the empirical evacuation response curve based on the traffic data collected in Cape May, New Jersey during Hurricane Irene. Hara and Kuwahara (2015) analyzed people’s behavior and traffic congestion patterns after the East Japan earthquake by using GPS data gathered from exploration vehicles and smart phones. The results provided key support for effective evacuation planning. Li et al. (2015) conducted a comprehensive analysis of spatio-temporal traffic patterns and highway disruptions during Hurricane Irene and Sandy evacuations in New Jersey. Hu et al. (2019) used vehicle trajectory data to investigate traveler’s behavioral responses to pre-planned events and examined the contribution factors. In addition to empirical travel behavior and traffic flows, previous studies have paid considerable attention to evacuation modeling and simulation, including static and dynamic models. A detailed review of evacuation modeling and simulation over the past decade can be found in Murray-Tuite and Wolshon (2013).

A few studies have investigated the relationship between human mobility and virus spread during the COVID-19 pandemic. Chinazzi et al. (2020) used a global collective population disease transmission model to predict the impact of travel restrictions on virus transmission. The results showed that the travel quarantine in Wuhan effectively delayed the overall progression of virus spread by 3 to 5 days in mainland China, and reduced case importations by nearly 80% until mid-February. Gan et al. (2020) proposed a framework to reflect the changes in the spatiotemporal distribution of exposure and transmission risk of COVID-19 based on human mobility in Shanghai. Huang et al. (2020) conducted a data-driven analysis of travel behaviors during the pandemic from the following perspective: (1) means of transportation, (2) types of venues to be visited, (3) check-in time at venues, (4) distance of “origin”, and (5) mode of “origin destination”; this study provided
decision-making support for better understanding of the impact of COVID-19 on traffic related behaviors, and it provided more targeted epidemic prevention measures. Neuburger and Egger (2020) examined the relationship between perception of COVID-19 and in travel risk perception and travel behavior among travelers in the DACH region (Germany, Austria, Switzerland). The results revealed a significant increase in the risk perception of COVID-19 and in travel risk perception over a short period of time. Oum and Wang (2020) examined the socially optimal lockdown and travel (social activity) restriction policies for communicable viruses including COVID-19. The results showed that in order to induce individual travelers to internalize the external costs of infection risks imposed on others and on the health care system, government action is necessary. Li et al. (2020) reviewed the basic structure and application of various epidemic spread models and suggested that there is a need for more in-depth research to examine the mutual feedback mechanism of epidemics and individual behavior. Engle et al. (2020) used GPS data from mobile phones in the US to show the effects of "stay-at-home" orders on human mobility. Therefore, there are sufficient studies to show that the travel behavior patterns of residents have changed during the pandemic.

As noted above, previous studies usually have focused on empirical travel behavior and traffic flow analysis in situations of natural disasters or adverse weather conditions. Very few studies have investigated the empirical urban traffic flow characteristics during a pandemic, due to the rare probability of such an event. Although several recently studies investigated the relationship between human mobility and virus spread during the COVID-19 pandemic, they have generally investigated the virus spread risk and the effects of travel restriction policies. There remains a research gap regarding the spatio-temporal characteristics of road congestion during and after the COVID-19 pandemic.

Research design

In this section, we introduced the basic situation of Shanghai. The traffic condition data provided by Baidu Maps is introduced. The average speed change rate is proposed to reflect the overall trend of spatio-temporal variations during the pandemic. The algorithm of singular value decomposition is applied to decompose the variations and analyze the spatio-temporal patterns of its components.

Study area and dataset

Study area

In this study, Shanghai is chosen as the study area. As a city that has largely controlled the pandemic and gradually resumed urban activity, it is of great significance to take Shanghai as a reference research. Shanghai is one of the most developed cities in China, with a total area of 6340.5 square kilometers and an urbanization rate of more than 80%. The population of Shanghai reached 24.28 million in 2019, of which more than 9.76 million are permanent immigrants—this statistic is relevant, because it indicates that Shanghai has frequent contacts with other cities. Both private and public transportation play an important role in Shanghai. According to the statistical data in 2019, the total length of urban roads in Shanghai is 5494 km, including expressway mileage more than 207 km. The number of cars has reached 5.4 million. The average daily trips are 57.1 million, including 5.71 million daily bus trips and 10.63 million trips using the subway system which comprises 18 lines.

The progression of the pandemic situation in Shanghai is shown in Fig. 1, the first case of COVID-19 was confirmed on 20 January, and the number of confirmed cases then increased rapidly. By the middle of February, the pandemic in Shanghai was well controlled. Although there were some imported cases in March, Shanghai's pandemic situation did not worsen, and was managed by means of strict measures, like centralized isolation for 14 days, and contact tracing by nucleic acid tests. The entire situation in Shanghai was basically under control in late March. Therefore, the study period of this research extends from 1 January to 15 March, 2020.

As the economic center of China, Shanghai is under great pressure to resume work and production. However, it should be noted that the start of Spring Festival holidays coincided with the emergence of COVID-19 in China. Many migrant workers had traveled back to their hometowns before the start of the travel ban on 23 January, 2020. After the extended Spring Festival holidays, according to Baidu Maps migration data2, three quarters of migrant workers had not returned from their holidays as usual because of the travel ban or home-based self-quarantine. All sectors in China were striving to resume work and production in an orderly manner. However, the shortage of migrant workers, the partial resumption of work from home, and the unresolved concerns about the pandemic made the resumption of work and production slower than expected. Similarly, the ridership of public transit did not immediately recover from the pandemic.

Dataset

The traffic condition data used in this paper is mainly provided by Baidu Map. The data was collected for the 446 traffic analysis zones (TAZs) in Shanghai from 1 January to 15 March, 2020. The data attributes and examples are shown in Table 1. In the process of data cleaning and preprocessing, considering that the intensity of night travel is always in a low level, records with missing attributes, as well as data collected from 10 p.m. to 5 a.m., was removed from the raw dataset.

2 https://qianxi.baidu.com/2020/.
Methodology

Average speed change rate

We set the traffic conditions of the TAZs in the last week before the first confirmed COVID-19 case as the baseline to represent the normal status before the pandemic outbreak. Then we assessed the variance between the baseline data and the traffic conditions of subsequent periods. According to Baidu Maps migration data, less than 25% of migrants who went back to their hometowns before the Spring Festival had returned to Shanghai by the first week of work resumption. The return rate was still lower than 50% in the second week, and it did not exceed 50% until the fifth week, so the study period can be divided into certain periods after work resumption on February 9th. The speed change rate was calculated in the first, second, and fifth weeks of work resumption. The rate can be calculated as follows, in which $v_i$ denotes the average speed of week one, two, or five, and $v_0$ denotes the average speed in the baseline data.

$$p = \frac{v_i - v_0}{v_0} \times 100\%$$ (1)

Singular value decomposition (SVD)

Matrix decomposition techniques are often used to extract features, including principal component analysis (PCA), singular value decomposition (SVD), non-negative matrix factorization (NMF), and related derivative algorithms, such as robust PCA and functional PCA, etc. (Chen et al., 2020; Lakhina et al., 2004; Ullah and Finch, 2013; Wang et al., 2012). The PCA problem can be transformed into an SVD problem in most cases, but using SVD is usually more stable than using PCA directly as it (SVD) avoids losing some accuracy when calculating the covariance. Additionally, SVD can obtain PCA results in two directions (row and column directions), which correspond to important temporal and spatial features in the specific problem. Compared with NMF, SVD does not need to determine the dimension after decomposition in advance. Also, NMF is a means of approximate reduction, while SVD is an accurate reduction method. For these reasons, we choose SVD as the feature extraction method.

Table 1
Attributes explanation of case data.

| Attributes       | Data Example          | Explanation                                           |
|------------------|-----------------------|-------------------------------------------------------|
| TAZ ID           | 1                     | ID of TAZ                                             |
| Label of Days    | holiday               | Workday/holiday                                       |
| Weekday Number   | 3                     | i.e., 1 for Monday, 2 for Tuesday, …                  |
| Label of Time Periods | morning peak         | Morning peak/evening peak/off-peak/other             |
| Timestamp        | 20200101007           | yyyMMddHH                                             |
| Congestion Index | 0.95401767            | The overall congestion level in the TAZ              |
| Congestion Mileage | 3.4952              | Mileage of congested roads in the TAZ (km)           |
| Average Speed    | 35.0434796            | Average speed in the TAZ (km/h)                      |
| Week Number      | 1                     | The number of weeks in the study period, i.e., the week of 1 January, 2020 is the first week |

Fig. 1. Reported cases in Shanghai.
The algorithm of SVD was applied to determine the inherent characteristics of the average speed in the TAZs. A spatio-temporal matrix $M = \{m_{ij}\}$ was constructed to represent the variation of traffic conditions. $m_{ij}$ refers to the average speed of roads in TAZ $j$ during the $i$-th time interval in the study period. Since the data collected from 10 p.m. to 5 a.m. was eliminated in the data preprocessing, every 16 time intervals represent one day in the study period. The formula of SVD as follows was applied to decompose the inherent characteristics of matrix $M$:

$$M = USV^T = \sum_{h=1}^{r} \delta_h u_h v_h^T$$

In the formula, $M$ is an $m \times n$ matrix, and the rank of $M$ is $r$. $U$ is the left singular matrix. It is an orthogonal matrix of $m \times r$, and $u_h$ is the $h$-th column of $U$. $V$ is the right singular matrix. It is a matrix of $n \times r$, and $v_h$ is the $h$-th column of $V$. $S$ is the diagonal matrix of $r \times r$. Diagonal elements of $S$ are singular values arranged in descending order, and the $h$-th element is the singular value $\delta_h$.

The spatio-temporal matrix $M$ is the collection of spatio-temporal variations influenced by multiple factors. After $M$ is decomposed by SVD, the left singular matrix $U$ reflects the variation patterns in the time dimension, and $u_h$ represents the $h$-th principal components in the temporal patterns of the traffic condition variation. Similarly, the right singular matrix $V$ reflects the variation patterns in the space dimension, and $v_h$ represents the $h$-th principal components in the spatial patterns. The singular value is positively correlated with the explanatory importance of the components. If we retain the first $k$ ($1 \leq k \leq r$) largest singular values and discard other smaller singular values, the most important $k$ components will remain and will to explain the spatio-temporal variation of traffic conditions during the pandemic.

**Results and discussions**

In this section, the overall trend of traffic conditions during the pandemic was analyzed based on the speed change rate proposed in this paper. SVD was applied to decompose the spatio-temporal matrix of traffic conditions. The most important components in the traffic condition variation were untangled and the spatio-temporal patterns of the different components were analyzed. Suggestions for the traffic management in mega cities during a pandemic are proposed based on the results.

**Results**

**The overall variation of road traffic conditions**

The average speeds in the TAZs in the different time periods during the first, second and fifth weeks of work resumption are compared with that of the set baseline. The speed change rates in the morning peak, evening peak, and off-peak periods are calculated and illustrated respectively, as shown in Fig. 2.

In the first week of work resumption, the change rates of average speeds in most TAZs were positive, indicating that the overall traffic conditions were significantly improved under the effect of the travel ban imposed because of the pandemic. However, with the pandemic under control, the government promoted the resumption of work and production, and the economy was recovering, which increased motorized travel. These factors caused the average speeds to gradually decline to the baseline level.

As illustrated in Fig. 2 and Fig. 3, the traffic congestion during peak hours gradually returned to the level it has been before the pandemic, which is more evident than that in the off-peak hours. This may indicate that the pandemic has changed travel behavior: many people reduced their travel overall, except for necessary commuting, and have chosen to drive private cars to reduce their risk of infection.

It should be noted that, as shown in Fig. 2, compared to the baseline, the average speeds of a few TAZs (shown as red zones in the Figs) in the far suburbs decreased significantly. This likely is the consequences of the comprehensive inspections at the entry points to Shanghai. All vehicles entering Shanghai must undertake a comprehensive inspection as part of ongoing measures to contain the spread of the pandemic.

**Spatio-temporal patterns and characteristics of the urban traffic**

The number of singular values obtained by SVD is the same as the number of rows in the spatio-temporal matrix, which represents many spatiotemporal patterns. Because spatio-temporal patterns that correspond to small singular values are not important and can only express the original spatio-temporal matrix to a very small degree, we chose the largest 50 singular values of the spatio-temporal matrix which are shown in Fig. 4. The horizontal axis of Fig. 4 represents the index of singular values in descending order. The vertical axis of Fig. 4 denotes the normalized singular value $\sigma_h$, which is defined as Eq. (3).

$$\sigma_h = \frac{\sigma_h}{\sum_i \sigma_i}$$
As shown in Fig. 4, the singular values of the matrix decrease sharply. The smaller the value, the less information its corresponding pattern reflects. The sum of the first three normalized singular values is 0.62. The information expressed by the first three singular values accounts for 60.2% of the original matrix, and the variation of the other singular values is very small. Therefore, the three most important components are identified from the spatio-temporal matrix based on the rank of singular values. The spatio-temporal patterns of the three identified components will be analyzed as follows.

Based on the return rate obtained from the Baidu Migration data, the study period was divided into five parts: from 1 January to 23 January, 2020 (normal status before the Spring Festival and travel ban); from 24 January to 9 February, 2020 (a) Morning peak (7 a.m. to 8 a.m.)
(b) Evening peak (5 p.m. to 6 p.m.)
(c) Off-peak (6 a.m. to 21 p.m. except for the morning and evening peak)

Fig. 2. Average speed change rate of three weeks in different peak.
2020 (the extended Spring Festival holidays); from 10 February to 16 February, 2020 (the first week of work resumption); from 17 February to 8 March, 2020 (the second to the fourth week of work resumption); and from 9 March to 15 March, 2020 (the fifth week of work resumption).

Fig. 5(a)–(c) illustrate the patterns of temporal variation. The fluctuating amplitude, direction of the curve (toward the positive or negative direction of the y-axis), and the sign of the value are the key factors. Fig. 6(a)–(c) illustrate the patterns of spatial variations. Cool colors and warm colors in the color bar stand for negative values and positive values in the TAZs. The temporal and spatial distributions need to be observed jointly to explain the meaning of each pattern. For example, if the temporal curve is positive and shows a significant positive fluctuation in some TAZs at some time while the spatial distribution values of these TAZs are negative, the average speed during the particular time period and the TAZs should significantly decrease. On the contrary, if the fluctuating direction of the temporal curve is negative, a significant increase in the average speed in these TAZs can be deduced.

The first principal component represents the relatively stable and main part of the variation. As shown in Fig. 5(a), under the combined influence of the travel restriction policy for the pandemic and the migration of people for the Spring Festival, the average speed shows a significant increase after the start of the Spring Festival holidays. The temporal curve does not exhibit evident peaks or troughs. As work and production resumed after 9 February, 2020, the curves gradually approach the blue one which represents the traffic conditions before. As shown in Fig. 6(a), there is no significant difference in the spatial distribution.

Fig. 3. Number of TAZs in different average speed change rate sections.

Fig. 4. Distribution of Normalized Singular Values of M.

The second principal component probably represents the part of the variation that was probably affected by commuting. As shown in Fig. 5(b), all five temporal curves show evident peaks during the commuting hours. With the increase in work resumption, the curves gradually approach the blue one during the peak hours. However, no significant change can be found in the off-peaks. As shown in Fig. 6(b), TAZs located within the Outer Ring Road and along the expressways are in warm colors. Since the spatial curves of these TAZs fluctuate toward the opposite direction of all temporal curves from 6 a.m. to 8 a.m. and from 12 p.m. to 17 p.m. in Fig. 5(b), the average speeds in these TAZs significantly decreased and reached their lowest values at about 8 a.m. (morning peak) and at about 17 p.m. (evening peak) respectively. On the contrary, the average speeds
increased in the TAZs in the outskirts of the urban areas in the morning and evening peaks. Pattern II shows that travel demand was reduced, except for necessary commuting needs.

The third principal component probably represents the part of the variation that was affected by the migrant population and the work resumption in certain other TAZs. As shown in Fig. 5(c), the fluctuation of the blue curve is not obvious before the pandemic. The fluctuation of curves in orange, green and red indicate that this part of the variation is only significant in particular periods of the days from 23 January to 8 March, 2020. Fig. 6(c) shows that this part of the variation appears in some certain particular TAZs. For example, the temporal curve, except the blue curve, had a noticeable positive fluctuation from 11 p.m. to 17 p.m., which means that the average speeds significantly decreased and reached their lowest values at around 17 p.m. in the TAZs in the cool colors. TAZs with a sharp decline of average speeds were mainly located in the city center and near the entry points of Shanghai. Three reasons are likely responsible for this decrease in speed. First, the unresolved concerns about the pandemic has forced more people to use private cars as their preferred mode of transportation. Second, restrictions on travel have weakened, so the amount of motorized travel has increased. Also, because of the work resumption, migrant people have been returning to the city. For congested TAZs near the entry points into Shanghai, the consequences of the comprehensive inspections at the entry points for all vehicles entering Shanghai have affected travel speeds.

Discussions

From the case of Shanghai, we can find that during the pandemic, traffic congestion was greatly alleviated due to the increase in telecommuting and the transfer of travel mode. While in the resumption period after the pandemic, congestion in the central urban area during the commuting peak hours gradually returned to normal levels. In the entry channel to Shanghai, caused by the influence of people returning to the city and to the strict pandemic prevention inspections, some congestion areas appeared. However, understanding the overall trends of the road network congestion patterns does not suffice to ensure a scientific basis for mobility management during the resumption period of COVID-19. The following suggestions are proposed to better manage and control urban mobility during and after a pandemic.

![Fig. 5. The temporal distribution of three patterns.](image-url)
First, it is necessary to conduct a more detailed questionnaire survey about travel behavior patterns during the COVID-19 pandemic, which combines the advantages of small sample size survey data for causal analysis and large spatial scale data analysis for macro situation analysis, so as to ensure the scientificity of traffic management during the resumption period. From the conclusions of our study, we find that the macro-data about the TAZs' average speed can be used to understand the traffic operation state during the pandemic, but there is a lack of further analysis regarding micro mechanisms and causality. For example, we found that traffic congestion during the morning and evening peaks gradually recovered to the level of the pre-pandemic period, but there was still a large gap during the off-peak period. However, based on the research presented in this paper, it is difficult to analyze the causes of this gap or to support the formulation and implementation of relevant traffic policies.

Second, the transfer of travel modes during and after the pandemic is a matter worthy of attention. During the outbreak stage, the overall travel frequency of residents decreased, and traffic conditions became better. It may be possible to encourage private travel by appropriately relaxing restrictions on cars and reducing or exempting parking fees to protect the basic needs of residents, so as to effectively supplement the transportation supply that was missing during the pandemic, and to maintain the normal operations of the city. In the post-pandemic stage, as the public transit system recovers, restrictions on cars could be tightened to force residents turn to public transit modes.

Third, it is important to understand the role of information technology in the urban transportation system during and after the pandemic. According to the results found in this paper, traffic congestion had an upward trend after the pandemic, which may be due to the trend of traffic mode transfer that occurred because of people’s concern about the virus transmission risk posed by using public transport. Therefore, it is necessary to improve the level of bus operation during a pandemic,
including shortening the departure interval on the premise of ensuring safety. Also, using Mobility as a Service (MaaS), customized busses and other means that provide personalized bus and travel services should be implemented.

Conclusions

The objective of this study is to investigate the empirical road traffic congestion patterns that occurred in Shanghai, China, during the COVID-19 pandemic. The hourly average speed data of TAZs from 1 January, 2020 to 15 March, 2020 was used. Based on the return rate of the city’s migrant population, the study period was divided into five periods. The last week before the Spring Festival holidays was set as the baseline. The speed change rate was used to assess the variance between the baseline data and the traffic conditions in other periods during the pandemic. The SVD algorithm was used to study the inherent composition of the spatio-temporal variation that was simultaneously influenced by several factors. The results are summarized as below:

(i) During the COVID-19 pandemic, the performance of traffic operations in Shanghai can be divided into two stages. At the outbreak stage of the pandemic (23 January–9 February, 2020), the average speed of the roadways in most TAZs increased significantly due to the combined effect of the pandemic and the Spring Festival holiday. As work resumed, the traffic operations in the peak hours gradually returning to the pre-pandemic level.

(ii) During the COVID-19 pandemic, the spatio-temporal variation of traffic operations in Shanghai can be divided into three principal components: the stable, main part of the variation; the part of the variation affected by commuting; and the part of the variation affected by the migrant population and pandemic during particular periods in particular TAZs.

(iii) To satisfy basic travel demands, during the outbreak stage of a pandemic, the restrictions on private car travel could be relaxed to supplement the missing public transit services. In the post-pandemic stage, the restrictions could be gradually restored to ensure the priority of public transit modes.

The methods proposed in this study help us to understand the dynamics of urban traffic operations in the complicated context of a pandemic outbreak. The conclusions can provide references for implementing differentiated management strategies. However, there remains a significant room for improvement in future works. For example, a travel behavior survey with a larger range could be conducted to compare travel behavior patterns before and after a pandemic. Combined with big data, the change in transportation systems could be further analyzed and interpreted. The SVD method implicitly assumes that observed data points come from a latent linear subspace, and thus can be approximated using a low-rank matrix (Verma et al., 2017). While data for work days and holidays may not lie in the same linear space, a nonlinear method could be adopted to enhance the interpretability of the results.

Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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