01 Mar 2022

Spatiotemporal Analysis of Urban Road Congestion during and Post COVID-19 Pandemic in Shanghai, China

Pengfei Xu

Weifeng Li

XianBiao Hu
Missouri University of Science and Technology, xbhu@mst.edu

Hangbin Wu

et. al. For a complete list of authors, see https://scholarsmine.mst.edu/civarc_enveng_facwork/2157

Recommended Citation

P. Xu et al., "Spatiotemporal Analysis of Urban Road Congestion during and Post COVID-19 Pandemic in Shanghai, China," *Transportation Research Interdisciplinary Perspectives*, vol. 13, article no. 100555, Elsevier, Mar 2022.
The definitive version is available at https://doi.org/10.1016/j.trip.2022.100555

Transportation Research Interdisciplinary Perspectives 13 (2022) 100555

Contents lists available at ScienceDirect

Transportation Research Interdisciplinary Perspectives

journal homepage: www.sciencedirect.com/journal/transportation-research-interdisciplinary-perspectives

Spatiotemporal analysis of urban road congestion during and post COVID-19 pandemic in Shanghai, China

Pengfei Xu [a,1], Weifeng Li [b,1], Xianbiao Hu [c], Hangbin Wu [d], Jian Li [e,*]

[a] Urban Mobility Institute, Tongji University, 4800 Cao'an Road, Shanghai 201804, China
[b] Key Laboratory of Road and Traffic Engineering of the Ministry of Education, College of Transportation Engineering, Tongji University, 4800 Cao'an Road, Shanghai 201804, China
[c] Department of Civil, Architectural and Environmental Engineering Missouri University of Science and Technology, Rolla, MO 65409, USA
[d] Associate Professor, Urban Mobility Institute, Tongji University, College of Surveying and Geoinfomatics, Tongji University, 1239 Siping Road, Shanghai 200092, China
[e] Associate Professor, Urban Mobility Institute, Tongji University, College of Transportation Engineering, Tongji University, 4800 Cao'an Road, Shanghai 201804, China

ARTICLE INFO

Keywords:
COVID-19 pandemic
Mobility behavior
Robust principal component analysis
Iterated cumulative sums of squares
Spatiotemporal heterogeneity

ABSTRACT

Coronavirus Disease 2019 (COVID-19) has become one of the most serious global health crises in decades and tremendously influence the human mobility. Many residents changed their travel behavior during and after the pandemic, especially for a certain percentage of public transport users who chose to drive their owned vehicles. Thus, urban roadway congestion has been getting worse, and the spatiotemporal congestion patterns has changed significantly. Understanding spatiotemporal heterogeneity of urban roadway congestion during and post the pandemic is essential for mobility management. In this study, an analytical framework was proposed to investigate the spatiotemporal heterogeneity of urban roadway congestion in Shanghai, China. First, the matrix of average speed in each traffic analysis zones (TAZs) was calculated to extract spatiotemporal heterogeneity variation features. Second, the heterogenous component of each TAZ was extracted from the overall traffic characteristics using robust principal component analysis (RPCA). Third, clustering analysis was employed to explain the spatiotemporal distribution of heterogeneous traffic characteristics. Finally, fluctuation features of these characteristics were analyzed by iterated cumulative sums of squares (ICSS). The case study results suggested that the urban road traffic state evolution was complicated and varied significantly in different zones and periods during the long-term pandemic. Compared with suburban areas, traffic conditions in city central areas are more susceptible to the pandemic and other events. In some areas, the heterogeneous component shows opposite characteristics on working days and holidays with others. The key time nodes of state change for different areas have commonness and individuality. The proposed analytical framework and empirical results contribute to the policy decision-making of urban road transportation system during and post the COVID-19 pandemic.

Introduction

The coronavirus disease 2019 (COVID-19) has spread worldwide with serious effects on human beings. Current studies show that the pandemic and travel behavior would influence and interact with each other (Huang et al., 2020; Neuburger and Egger, 2020; Oum and Wang, 2020). Since human mobility, especially those based on public transport, is an important underlying factor for the rapid spread of the virus during the COVID-19 outbreak period. People may change their travel behaviors from public transport to individual automobile due to health threat (Arimura et al., 2020; Beck et al., 2020; Fatmi, 2020). Thus, urban road traffic congestion patterns during and after the COVID-19 pandemic are significantly different to previously daily patterns. For example, according to the results of the survey on the post-pandemic travel behavior in Shanghai, around 82% of respondents who used to take public transport have shifted to private transport modes for commuting (Wang et al., 2021).

Current studies usually focused on urban roadway congestion

* Corresponding author.
E-mail addresses: 1651250@tongji.edu.cn (P. Xu), liweifeng@tongji.edu.cn (W. Li), xbhu@mst.edu (X. Hu), hb@tongji.edu.cn (H. Wu), jianli@tongji.edu.cn (J. Li).
[1] Pengfei Xu and Weifeng Li are co-first author. Both authors contributed to this paper equally.

https://doi.org/10.1016/j.trip.2022.100555
Received 23 July 2021; Received in revised form 26 November 2021; Accepted 29 January 2022
Available online 3 February 2022
2590-1982/

patterns during relatively short-term non-recurrent incidents such as natural disasters, adverse weather and so on (Anbaroglu et al., 2014; Güner et al., 2012; Li et al., 2015; Skabardonis et al., 2003). However, compared with natural disasters or adverse weather conditions, the impact of pandemics may last longer, e.g., months or even years, and roadway congestion patterns could be affected by multiple factors, including pandemic prevention strategies, work resumption orders and so on (Jun 2010; Xu et al., 2019; Liu and Sharma, 2006; Nian et al., 2020; Xu et al., 2020). Our previous study (Li et al., 2021b) investigated the spatial heterogeneity of urban roadway congestion during the pandemic. The inherent composition of urban road congestion patterns was identified using the temporal distribution of hourly average speed in different TAZs. However, the impact of pandemics on urban roadway congestions is not evenly distributed in both time and space. Actually, the spatiotemporal heterogeneity of urban roadway congestion is more important for mobility management during and post a pandemic.

This study aims to investigate the spatiotemporal impact of multiple factors on the road network, which contains both homogeneity and heterogeneity components. The former represents similar variation trend for all TAZs, while the latter represents spatiotemporal heterogeneous characteristics for different TAZs. A modeling framework is proposed to reveal the spatiotemporal homogeneity and heterogeneity of the transportation system characteristics. The proposed framework first constructs a spatiotemporal speed matrix. Next, the homogenous and heterogeneous components from overall traffic state variations are separated. Then, a clustering method is used to all TAZs into several clusters with similar heterogeneous traffic characteristics to understand the heterogeneous spatial distribution. Finally, the series analysis method is used to determine the temporal characteristics for each cluster. An empirical study of Shanghai is conducted using speed data of TAZs collected in the first half of 2020. The change in heterogeneous traffic conditions of Shanghai during and after COVID-19 is revealed and analyzed based on the proposed framework.

Several features distinguish this study from previous ones. First, though previous studies have explored the role of the transportation system in infectious diseases like H1N1 (Lowcock et al., 2012; Xiao et al., 2011; Xu et al., 2019), SARS (Yoneyama et al., 2010), etc., the influence scope and degree of these diseases are far less than that of COVID-19. In addition, these studies mainly discussed the effect of the transportation system in virus transmission by mathematical models (Li et al., 2021a), but few studies explored the congestion variations of road network under a pandemic. In this paper, an analytical framework was proposed to assess the temporal and spatial impacts of the COVID-19 pandemic on Shanghai Road network. The proposed framework can be used in other similar cities under the COVID-19 or similar pandemic conditions in future.

Second, previous studies mainly focused on road network conditions under respectively short-term non-recurrent incidents, e.g. adverse weather, traffic accidents (Anbaroğlu et al., 2015; Li et al., 2013; Zhao et al., 2019), while study period in this work is six months from January to June 2020, including three stages: the pre-pandemic period, the outbreak period, and the resumption period, which comprehensively reflects the long-term impact of several factors on the transportation system during the pandemic.

Third, previous studies usually decomposed high-dimensional OD matrices under a certain travel mode to obtain the main travel composition (Duan et al., 2018; Lakhina et al., 2004), but it is hard to collect origin–destination (OD) in the whole city level, and the results cannot fully reflect road congestion variations. In this paper, robust principal component analysis (RPCA) algorithm was used to extract the homogeneous and heterogeneous components from original speed matrix effectively. The results show that RPCA algorithm has strong adaptability to the data with sharp noise.

This paper is structured as follows: Section 2 provides a brief review of related work; Section 3 introduces the study area and the data; Section 4 presents the proposed framework and the methods; Section 5 presents the results; Section 6 presents discussion of results and suggestions for future research to address the limitations of this study; Section 7 summarizes conclusions.

Literature review

Previous studies usually focused on traffic patterns during or after non-recurrent traffic events such as natural disasters and adverse weather conditions to better minimize the negative impact on urban systems. For example, Wolshon and McArdle (2009) illustrated the extent to which the evacuation impacted the road traffic conditions in Louisiana following Hurricane Katrina. Hara and Kuwahara (2015) focused on the human mobility patterns and their impacts on traffic congestions after the East Japan earthquake, emphasizing the importance of probe data in disaster mitigation planning. Li and Chen (2014) investigated the non-recurrent freeway congestions caused by rainstorms. Polson and Sokolov (2017) developed a deep learning model and predicted the traffic flow of an interstate during an extreme snowstorm event. Umeda et al. (2019) analyzed the traffic state of a commercial vehicle from a macroscopic viewpoint by using the probe data gathered in western Japan during a period of heavy rain. In addition to the empirical analysis of traffic patterns, considerable attention has been paid to evacuation modeling and simulation. A comprehensive review about highway evacuation models over the past decade can be seen in Murray-Tuite and Wolshon (2013).

During the outbreak period of COVID-19, transportation systems had a great significance on blocking virus spread. Governments issued transport policies, including travel restrictions, road closures and public transit outages to reduce residents' travel and the infection risk. Sufficient studies have demonstrated that COVID-19 has changed residents' mobility pattens and travel behavior, which would further affect the characteristics of urban road traffic. Gan et al. (2020) explored the different patterns of COVID-19 pandemic risk on a 500 $\times$ 500 m spatial scale. The results suggested that areas and nodes such as city centers, airports and railway stations with high mobility have a greater risk of infection. de Haas et al. (2020) analyzed the impact of "intelligent lockdown" on people's activities and travel behavior. The results showed that around 80% of residents reduced their outdoor activities. Chinazzi et al. (2020) evaluated the benefits of travel limitations on the spread of COVID-19 in terms of national and international based on the proposed model. Oum and Wang (2020) showed that government actions like travel restrictions via lockdown or monetary penalty are necessary during communicable viruses including COVID-19. Engle et al. (2020) combined GPS data with COVID-19 case data and other demographic information to estimate how "stay-at-home" orders influence the local infection rate.

Road traffic patterns during a pandemic are different from those disasters such as earthquakes, hurricanes, rain storms etc. Due to the rare probability of a pandemic, the characteristics of road traffic during such an event has received insufficient attentions. Although some recent studies have investigated the interaction between travel behavior and COVID-19 spread, this has been predominantly through the establishment of mathematical models or multi-agent simulation to calculate the risk of infection. A detailed review of various epidemic spread models can be found in the work of Li et al. (2021). Thus, there remains a lack of research on the road traffic spatiotemporal characteristics during and after the COVID-19 pandemic.

Study area and data

Shanghai was selected as the case study area. Shanghai is the center of finance, trade, shipping, and technological innovation in China, and an emerging global city in worldwide. As an international megacity with more than 24 million residents, Shanghai faced significant challenges during and post the pandemic. Although the pandemic has been well under controlled by strict measures by local government, many residents changed their travel behaviors from bus/transit to automobile. The increased automobile usage has been causing significant roadway congestions.

The data used in this study was provided by Baidu Maps. The data sample are shown in Table 1. The hourly average speed data was collected in terms of traffic analysis zones (TAZs) in Shanghai from January 1 to June 15, 2020. Fig. 1 shows the spatial distribution of 439 TAZs based on 16 administrative districts. The purple zone is the urban central area of Shanghai is surrounded by an outer ring road. In this study, we mainly focused on the daytime road traffic patterns between 6 a.m. and 9p.m.

The pandemic situation in Shanghai has experienced a tortuous process. Fig. 2 shows the timeline of the pandemic developments in Shanghai. The first case was confirmed on January 20, and then the first-level emergency response was issued by the government on January 25[2]. In accordance with the law on the prevention and treatment of infectious diseases, the measures on the prevention and control of the COVID-19 outbreak had been taken in the transportation system of Shanghai, as illustrated in Fig. 3. Although the number of confirmed local cases gradually stopped increasing, the Spring Festival holiday was extended by 5 days to February 9 to control the risk of the pandemic spread. Despite of some imported cases, the whole situation in Shanghai has been basically under control in late February. The emergency response level was lowered to level 2 on March 23 and downgraded to level 3 on May 3.

Along with the COVID-19 developments before late March, three main factors are supposed to simultaneously affect the social and economic operation in Shanghai, as well as the transport operation. They are the unusual human migration after the Spring Festival holidays, the reduced public life during the pandemic, and the resumption of work and production.

First, the start of Spring Festival holidays coincided with the emergence of COVID-19. Migrant workers had traveled back to their hometowns before the start of the travel ban on January 23. Three quarters of the migrant workers had not returned from their holidays as usual because of the travel ban or home-based self-quarantine.

Second, the extended Spring Festival holidays were outbreak-control closure periods for social distancing. From the perspective of urban transport, with the reduced public life came the decreasing travel demand especially in the public transport systems.

Finally, after the Spring Festival holidays, all sectors in Shanghai were striving to resume work and production in an orderly manner. However, the shortage of migrant workers, the partial resumption of work at home and the unresolved concern of pandemic made the resumption of work and production slower than expected. From the perspective of intracity travel demand, the travel demand did not recover immediately until the whole situation in Shanghai was basically under control and the resumption of work accelerated in March.

Table 1
Data sample and attributes.

Attributes	Data sample	Explanation
ID	20	ID of TAZ
Days Label	Workday	Workday or holiday
Weekday Number	2	1 for Monday, 2 for Tuesday, …
Time Periods Label	p.m. peak	a.m. peak/p.m. peak/off-peak/other
Timestamp	2020–02-01–08	Yyyy-MM-dd-HH
Traffic Index	0.72491	The congestion level in the TAZ
Congestion Mileage	4.1024	Congested mileage in the TAZ (km)
Average Speed	36.05267	Average speed of the TAZ (km/h)
Week Number	2	The week of 1 January 2020 is the first week, …

[2] According to “contingency rules of paroxysmal public health events”, public health emergency events are classified into four levels, with severity decreasing from Level 1 to Level 4.

Methodology

Framework

Fig. 4 presents the methodological framework of this study. The framework includes four main steps:

Step 1. Spatiotemporal speed matrix calculation: calculate matrix $M = \{m_{ij}\}$ to reflect the variation of roadway speeds, where m_{ij} is the average speed of all links in TAZ i during the j-th hour.
Step 2. Spatiotemporal speed matrix decomposition: identify the heterogeneity component from the overall traffic characteristics in spatiotemporal matrix with RPCA. The sparse matrix $S = \{s_{ij}\}$, obtained by decomposition, reflects the heterogeneity of the TAZs.
Step 3. Identification of heterogeneous groups: categorize TAZs with similar heterogeneity to explore the spatial and temporal distribution characteristics by using K-means clustering method.
Step 4. Analysis of the fluctuation characteristics of heterogeneity: find structural break points of the cluster center series by using iterated cumulative sums of squares (ICSS) to understand the temporal variation patterns of heterogeneity.

Separation of heterogeneity component in traffic characteristics

Matrix decomposition is a common way to extract features from original data (Chen et al., 2020; Hu et al., 2019; Lakhina et al., 2004; Ullah and Finch, 2013; Wang et al., 2012). Common matrix factorization methods include Non-negative Matrix Factorization (NMF), Principal Component Analysis (PCA), and Singular Value Decomposition (SVD), etc. NMF can only be used for non-negative matrices and obtain the base matrix and coefficient matrix after dimensionality reduction, but it cannot reconstruct the original matrix based on several important components. SVD and PCA are almost same in most cases (Gerbrands, 1981). They lay down the foundation to untangle data into independent components. While PCA cannot provide ideal results when the data are large and contain much noise, RPCA is able to recover essentially low-rank data from large and contaminated data. The robust principal component analysis algorithm (RPCA) is applied to decompose the original spatiotemporal matrix of the average speed M.

Given M, the RPCA algorithm takes the matrix M as the sum of a low-rank matrix L_0 and a sparse matrix S_0 (most elements of the matrix are zero). From the perspective of transportation, the low-rank matrix L_0 reflects shared variation characteristics for all TAZs, while the sparse matrix S_0 reflects spatiotemporal heterogeneous characteristics for different TAZs influenced by several factors. L_0 and S_0 are solved by Eq. (1). The basic idea of RPCA is to balance the two optimization objectives (minimizing the rank of L and the number of non-zero elements of S) by coefficient λ. Considering that 0-norm (the number of non-zero elements) is discontinuous, 0-norm is replaced by 1-norm (sum of absolute values of elements)

$$\min_{L,S} \|L\|_* + \lambda \|S\|_{1,1} s.t. L + S = M \tag{1}$$

RPCA requires that the low-rank matrix L_0 should not be too sparse and the sparse matrix S_0 should not be low-rank (Candes and Plan, 2010). To guarantee L_0 is not a sparse matrix, the original matrix M should not be sparse, and to ensure that S_0 is not low-rank, there should be enough events in the study period. For this study, the original average speed matrix of the TAZs is clearly not sparse and the study period is long enough to contain many events. The objective function of RPCA

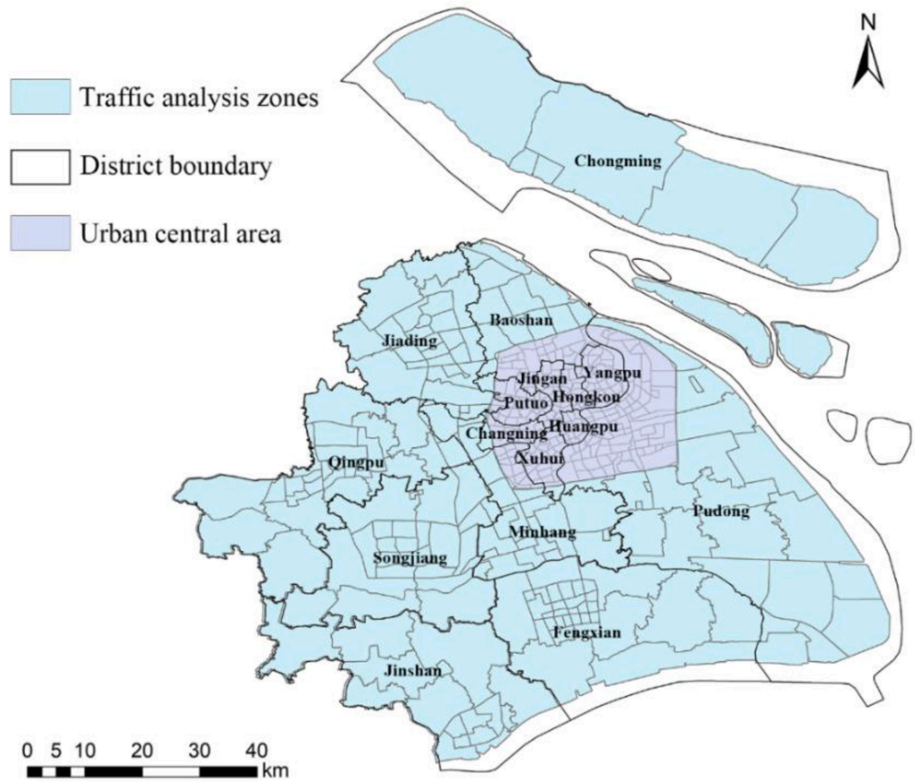


Fig. 1. Study area.

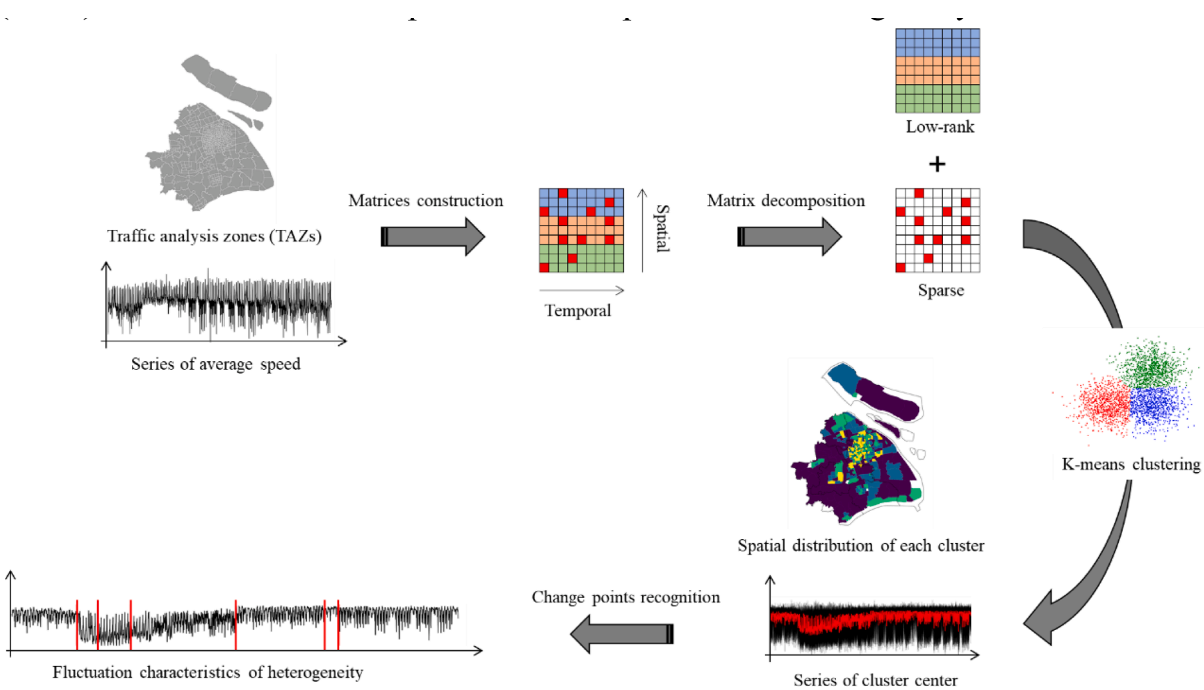


Fig. 2. A timeline of COVID-19 developments in Shanghai.

needs to be written in the form of Eq. (2) by Lagrange multiplier, where μ is a penalty parameter to ensure the convergence of the algorithm:

$$\min_{L,S} \|L\|_* + \lambda \|S\|_{1,1} + < Y, M - L - S > + \frac{\mu}{2} \|M - L - S\|_F^2 \tag{2}$$

For the matrix of $n_1 \times n_2$, the recommended value of μ can be calculated via the following equation, in which σ is the variance, and that the elements in the error matrix obey the same and independent normal distribution.(Zhou et al., 2010)

$$\mu = \sqrt{2\max(n_1, n_2)}\sigma \tag{3}$$

The recommended value of λ can be computed via Eq. (4) below:

$$\lambda = 1/\sqrt{max(n_1, n_2)} \tag{4}$$

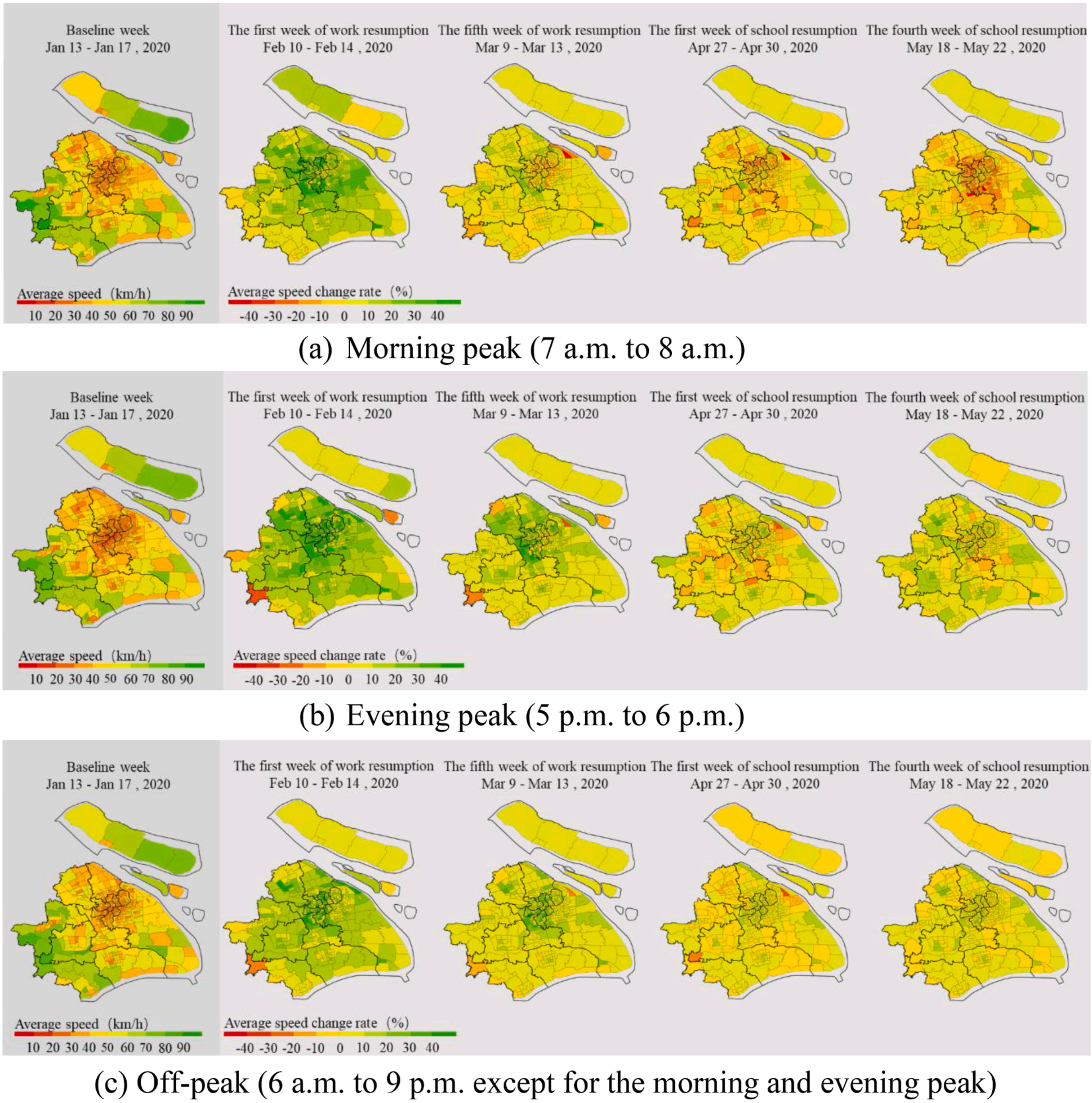


Fig. 3. Preventive & control measures applied in the transportation system in Shanghai (by March).

With these parameters determined, the Iterative Thresholding algorithm is then applied to solve this convex optimization problem.

Classifying TAZs by heterogeneity component

The K-means clustering algorithm is employed to determine the clusters of TAZs with similar heterogeneous traffic characteristics. Taking the sparse matrix S_0 obtained in Section 3.2 as the heterogeneity of variations for all TAZs, K-means clustering is used to determine the number of heterogeneous scenarios.

The key problem of clustering is the similarity index and the number of clusters. For the selection of similarity index, Euclidean distance is compared between two TAZs of average speed data, i.e., to compare the Euclidean distance between the rows of sparse matrix S_0. Since the time and space complexity of K-means are O(n), clustering the rows of S_0 is not a time-consuming work.

Fluctuation analysis of heterogeneity component

The algorithm of Iterated Cumulative Sums of Squares (ICSS) (Inclan and Tiao, 1994) is used to analyze the fluctuation characteristics of heterogeneity component for each cluster and can identify the mutation of sequence variance to search structural breaks. ICSS is based on the central cumulative sum of squares (Brown et al., 1975). First, we define the logarithmic speed change rate as:

$$r_t = \log v_t - \log v_{t-1} \tag{5}$$

where v_t denotes the average speed of either TAZ in t-th time interval. The constant term is removed:

$$r_t = b + a_t \tag{6}$$

where a_t is an uncorrelated random variable with mean zero and variance σ_t^2, t = 1, 2, …, T. $C_k = \sum_{i=1}^{k} a_t^2$ the cumulative sum of squares for a_t and consider its normalized form:

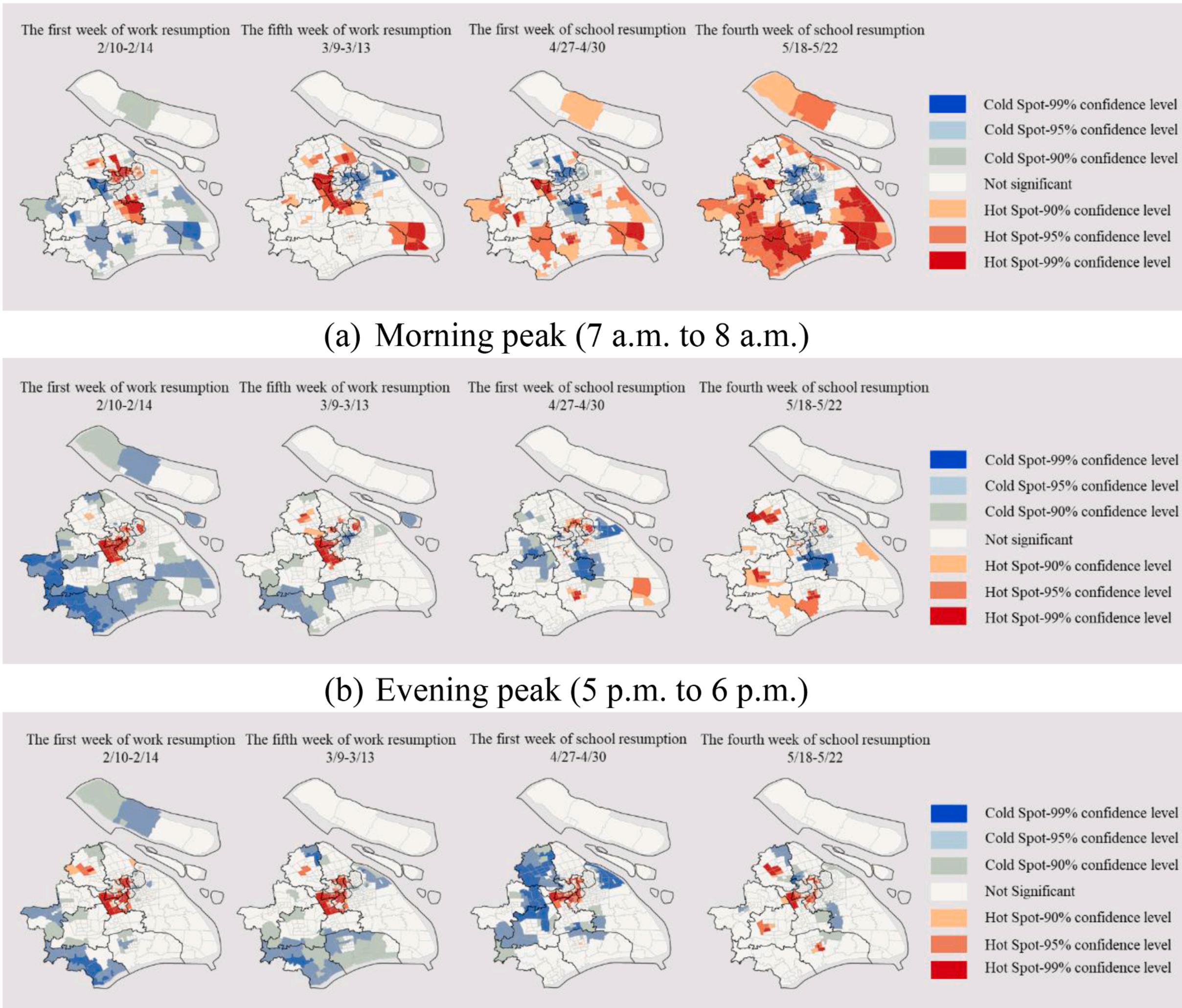


Fig. 4. Framework of the methodology.

$$D_k = C_k/C_T - k/T, k = 1, \cdots, T, \text{with} D_0 = D_T = 0$$

If the maximum value of $\sqrt{T/2}|D_k|$ is greater than the critical value, there is a variance change point, and its location is the moment of structural change in volatility. This method can also be used to examine multiple change points when a major structural break can mask the impacts of other change points. The pseudo-code of the ICSS algorithm is shown below.

Algorithm 1 Iterated cumulative sums of squares (ICSS)

Input: Series length T, critical value D^*(confidence level: 0.95)

$t_1 = 1$, $Q = \varnothing$, $k_{first} = 1$, $k_{last} = T$,
while $k_{first} < k_{last}$: {
  $k^* = \text{argmax}(|D_k(a[t_1 : T])|)$
  $k^*_{copy} = k^*$, $t_2 = k^*$
  $M(t_1 : T) = \sqrt{(T - t_1 + 1)/2}|D_k(a[t_1 : T])|$
  if $M(t_1 : T) > D^*$:
    $Q = Q \cup \{k^*\}$ //consider that there is a change point in k^*.
    while $M(t_1 : t_2) > D^*$: {
      $t_2 = k^*$
      $M(t_1 : t_2) = \max \sqrt{(t_2 - t_1 + 1)/2}|D_k(a[t_1 : t_2])|$
      $k^* = \text{argmax} (|D_k(a[t_1 : t_2])|)\}$ //$t_1 \le k \le t_2$
      $k_{first} = t_2$
      while $M(t_1 : T) > D^*$: {
        $t_1 = k^*_{copy} + 1$

(continued on next column)

(continued)

Algorithm 1 Iterated cumulative sums of squares (ICSS)

        $M(t_1 : T) = \max\left(\sqrt{(T - t_1 + 1)/2}|D_k(a[t_1 : T])|\right)$
        $k^*_{copy} = \text{argmax} (|D_k(a[t_1 : t_2])|)\}$ //$t_1 \le k \le T$
      $k_{last} = t_1 - 1$
      if $k_{first} = k_{last}$: //there appears only one change point.
    end while
    $Q = Q \cup \{k_{first}\} \cup \{k_{last}\}$
    $t_1 = k_{first} + 1$
    $T = k_{last}$
    if $M(t_1 : T) \le D^*$:
      end while
}
Output: Change points Q.

Results

The overall road congestion variation

The weekdays between January 13, 2020, and January 17, 2020, were the last five weekdays before the first confirmed case in Shanghai. Affected by the pandemic, the time range of the Spring Festival is from

Jan 24 to Feb 9, 2020, which is extended 9 days compared with normal conditions. Baidu migration[3] data can reflect the travel trends of a city population, providing an important reference for scientific pandemic prevention and work resumption. If there is no pandemic, the work and school resumption after the Spring Festival should be very rapid, while through the migration and statistic data, we find that the population return process lasts for a long time.

To fully reflect the impact of the pandemic and eliminate the interference of the Spring Festival, the traffic conditions of Jan 13 to Jan 17 were set as the baseline to represent the pre-pandemic congestion level. According to migration data and important timing scheduled by the government, we chose four stages listed below, and calculated the average speed change rates to observe the overall change of road traffic in the whole study period.

Stage 1: February 10- February 14, 2020, the first week of official resumption of work (the return rate of city dwellers[4] who left shanghai before the Spring Festival was less than 25%);
Stage 2: March 9 - March 13, 2020, the fifth week of work resumption (the return rate first exceeded 50%);
Stage 3: April 27 - April 30, 2020, the first week of school resumption (the first batch of students resumed classes);
Stage 4: May 18, 2020 - May 22, 2020, the fourth week of school resumption.

The change rate is calculated as follows, where v_i is the daily average speed of a certain stage and v_0 is the daily average speed of the baseline week:

$$p = \frac{v_i - v_0}{v_0} \times 100\% \tag{8}$$

Fig. 5 shows the overall variation of traffic congestions during the study period. At the beginning of work resumption, the impact of the pandemic on urban roadways was far from over, so the overall traffic conditions improved obviously. With the pandemic under control, work and school resumed, and the congestion gradually returned to the baseline level, while some TAZs in the central city area were even more congested than the baseline week, which may be due to people's fear of transmission on public transit. It should be noted that the average speed of some red TAZs in the far suburbs decreased significantly at the beginning of work resumption. This may be due to careful and thorough inspections at the entry highways where vehicles entering the city were required to undertake a set of strict quarantine measures to contain the pandemic.

The Getis-Ord Gi* statistics was also used to identify statistically significant spatial clusters of high values (hot spots) and low values (cold spots) in Fig. 6. A warm color represents spatial clusters with high change rate, indicating that traffic conditions in these TAZs improved significantly. A cold color represents spatial clusters with low change rate, indicating that the traffic conditions in such areas significantly deteriorated. The darker the color in the warm and cold TAZs, the more significant the degree of clustering of high or low values.

The overall changes of traffic congestion in the study period can be further understood by combining in Fig. 5 and Fig. 6. For instance, for results of morning peak and evening peak, the traffic conditions in the urban area improved significantly compared to the baseline week in the early stage of work resumption, while the traffic conditions in the suburbs (including the highway crossings around the provincial border and some suburban new cities) had no obvious improvement trend, and even deteriorated for few TAZs. With the resumption of work and school, the traffic conditions in the central area during the morning rush hour were still better than before the pandemic, but the traffic conditions in the outer areas of the city center had deteriorated significantly, and the scope of deterioration continued to expand, with traffic conditions in the suburbs basically reaching the level before the pandemic. Generally speaking, first, the congestion recovery speed in the central area in the morning and evening peak is significantly faster than that in the suburbs; second, the recovery trend of congestion in the off-peak is obviously weaker than that in the morning and evening peak.

Homogeneity component of congestion variation patterns

The results of hot and cold spot analysis indicate that the distribution of impacts on traffic operation is not uniform. Therefore, the RPCA algorithm was used to decompose the spatiotemporal matrix into low-rank matrix and sparse matrix. The low-rank matrix reflects the homogeneity component or general variation characteristics for all TAZs under the influence of a series of factors, including the pandemic, holidays, work and school resumption, etc.

Fig. 7 shows the average value of low-rank matrix of TAZs in each stage. After the pandemic was well controlled, the homogeneity of road traffic variations was in an obvious deterioration trend during the work and school resumption. For the off-peak period, the degree of deterioration was smaller than in the peaks. The rank of matrix reflects the correlation between rows or columns. Since the number of rows in low-rank matrix is 439 and the rank of the matrix is 37, it means the change trends of most TAZs are consistent. In general, for more than 90% of the TAZs affected by the pandemic, the average speed increased and the traffic condition improved at the beginning of work resumption. With the pandemic under control and the economy in recovery, the traffic congestion gradually deteriorated to the baseline level.

Identification of heterogeneous scenarios

Contrary to low-rank matrix, the sparse matrix obtained by decomposition reflects the spatiotemporal heterogeneity component under the influence of several factors. The sign of the value in the sparse matrix reflects the direction of the influence on the average speed: a positive sign indicates that the speed is positively affected, and a negative sign indicates that the speed is negatively affected by multiple factors. The absolute value reflects the degree of the impact.

By performing K-means clustering on the rows of the sparse matrix, the TAZs with similar heterogeneity characteristics could be grouped together. The elbow method was used to search for the optimal number of clusters. Four clusters of time series are drawn in Fig. 8, and the corresponding spatial distributions of TAZs are drawn in Fig. 9. The black curve in Fig. 8 represents the time series with hourly time intervals, which is the row of the sparse matrix corresponding to TAZs in each cluster, and the red curve is the cluster center.

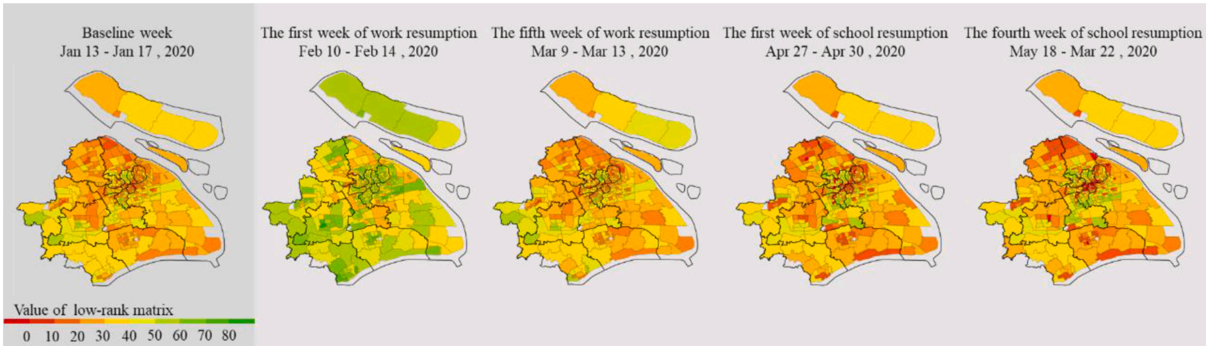
The four clusters experienced some abnormal fluctuations under the influence of factors such as the pandemic and holidays, but with the resumption of work and production, their fluctuations gradually returned to pre-pandemic levels. From the spatiotemporal distribution in Fig. 8 and Fig. 9, we have some interesting findings as follow:

For cluster 1: During the whole study period, the traffic conditions continued to be positively affected with little fluctuation in the degree of impact during and after the pandemic. These TAZs were located in suburban areas and along the outer ring road. Compared with the central area, the daily traffic volume is smaller, so the degree of impact in these areas is also smaller.

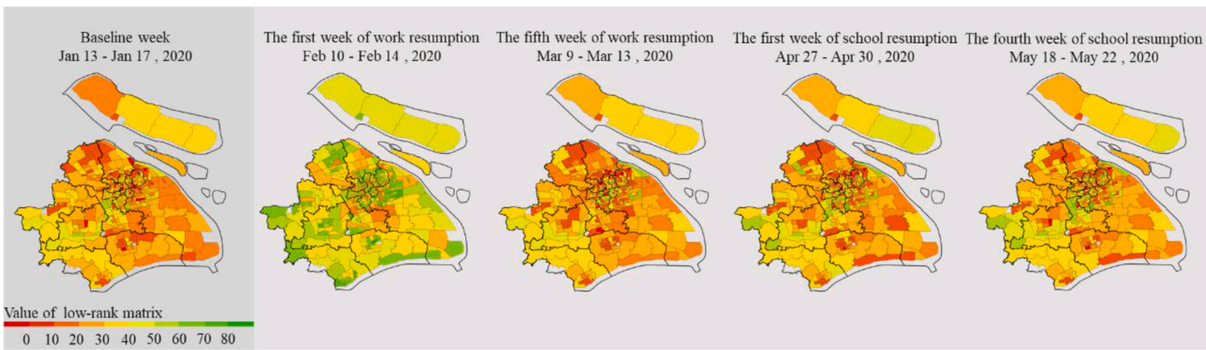
For cluster 2: During the outbreak period, public transit was restricted and private cars are more used, which leads to a negative effect around the Spring Festival holiday. During the resumption periods, working days were positively affected, holidays were negatively affected, and the negative effects continued to weaken. From the spatial distribution and fluctuation characteristics, we can infer that these TAZs are areas where the workplace is concentrated. With the resumption of

[3] https://qianxi.baidu.com/

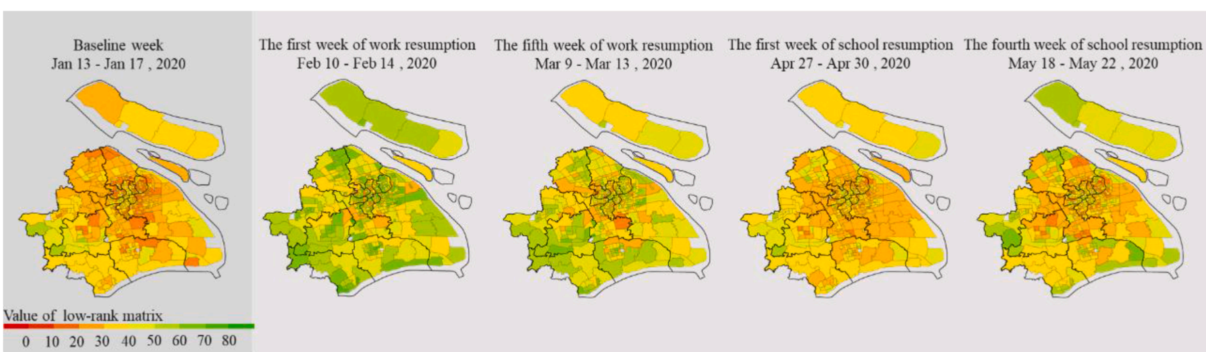
[4] The ratio of the population moving back after the Spring Festival holiday to the population moving out before the holiday.



(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 9 p.m. except for the morning and evening peak）

Fig. 5. Average speed change rate in four stages.

work, the heterogeneity fluctuation gradually returned to pre-pandemic level.

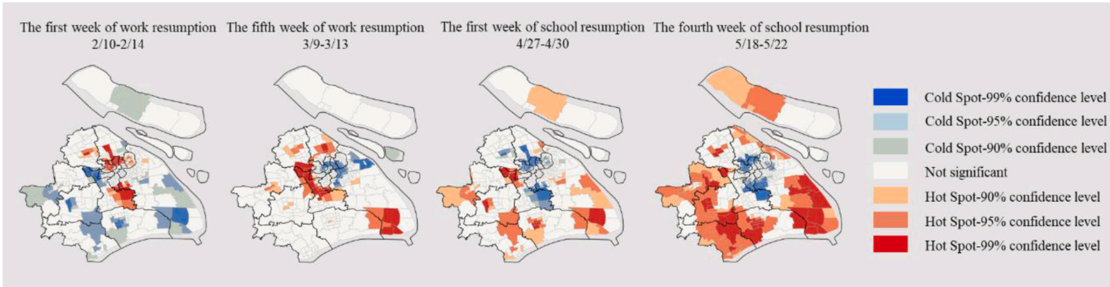
For cluster 3: Similar to cluster 2, there is a negative effect around the Spring Festival holiday. During the resumption periods, working days were positively affected, holidays were negatively affected, and the effects did not change much. Most of these TAZs were concentrated in the center of the city, and a small number are distributed in the suburbs. This cluster was mainly related to the workplace. Since the commuting demand is rigid, the heterogeneity part has strong periodicity.

It is worth noting that, for cluster 2 and cluster 3, the fluctuation of working days and weekends became chaotic after the middle of May, which may indicate that there is still room for the congestion on working days to further worsen in these areas.

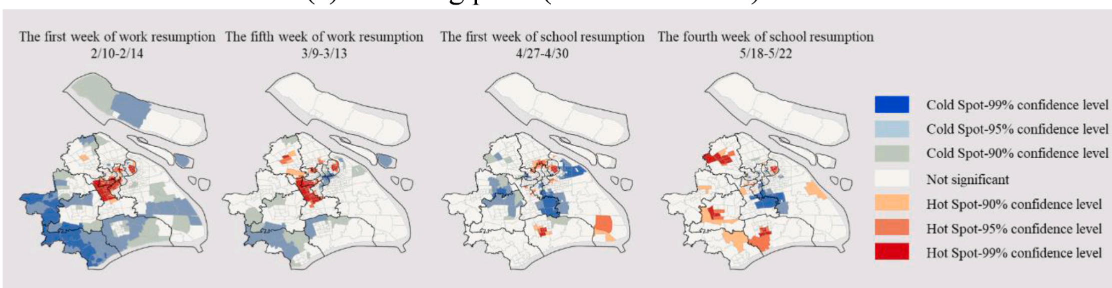
For cluster 4: Travel restrictions alleviated congestion greatly during the outbreak stage. During the resumption periods, working days were negatively affected, holidays were positively affected, and the negative impact of working days continued to increase. These TAZs were generally distributed in the city center and in the west of the Huangpu River, where a large number of residential areas are concentrated. The continuous increase of congestion on working days may be due to the transfer from public transit to private cars under the influence of the pandemic. With the work resumption, these areas would bear greater congestion pressure in the morning and evening peaks of the working day.

Fluctuation characteristics of heterogeneity

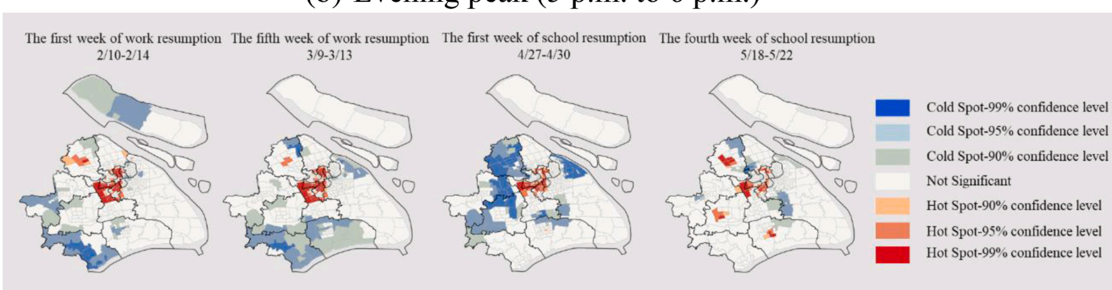
To further analyze the heterogeneity fluctuation characteristics, the ICSS algorithm was used in the center of four clusters respectively to discover the change points of the series. As shown in Fig. 10, the road traffic performance presents various characteristics in different periods. Although the locations of specific change points were diverse in different clusters, there were several shared change points for all clusters. Some of these points were caused by the natural fluctuations in weekends and peak hours, and the other change points were caused by global factors such as the pandemic and Spring Festival holiday, including the points detected around January 15 (the week after the Spring Festival travel season and before the Spring Festival, a large number of the population



(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 9 p.m. except for the morning and evening peak）

Fig. 6. Spatial clustering of high value and low value with statistical significance.

left Shanghai to return to their hometowns), around January 30 (the time when the Spring Festival holiday normally ended, a large number of the migrant population returned to Shanghai), and around February 22 (the beginning of large-scale work and production resumption).

Further, some clusters had their own unique change points. Cluster 1 had the least change points, which indicated that the state of these TAZs fluctuated little during the whole pandemic period. April 29 divides work resumption into two periods in cluster 1. From the identification results of structural change points in cluster 2, February 20, March 18 April 14, and April 29 were key traffic nodes, indicating that in these areas, with the resumption of work and school, the positive impact on working day and the negative impact in holiday were gradually weakening. The change points distribution of cluster 3 before March 18 was almost the same as that of cluster 2. For cluster 4, TAZs were mainly located in the central area, which was greatly affected by commuting traffic. Therefore, there was a more intensive distribution of structural change points before and after the Spring Festival holiday in this cluster. The change point within the Spring Festival happened to be the boundary between the normal Spring Festival holiday (January 24, 2020 - January 31, 2020) and the extended holiday (February 1, 2020 - February 9, 2020) in response to the pandemic. With the resumption of work, production, and school, the positive impact on working day traffic became weak, with February 29 and the Tomb Sweeping Festival holiday as two key nodes.

Discussions

From the case of Shanghai, the increase in telecommuting and the transfer of private travel modes greatly alleviated urban road congestion during the pandemic. While in the resumption period, congestion in the central urban area during the commuting peak hours gradually reached pre-pandemic levels. Furthermore, the variation of road traffic condition influenced by multiple factors have both similarities and spatiotemporal heterogeneity. An in-depth analysis of the latter is conducted in this study. However, understanding the road traffic congestion evolution patterns may not be sufficient to provide a scientific basis for mobility management during the resumption period of the COVID-19 or other epidemics. The following suggestions are proposed to better manage and control urban mobility during and after a pandemic:

First, a more detailed survey in travel behavior patterns during and after the pandemic is necessary. Survey data have advantages for casual analysis, while large-scale traffic condition data are suitable for macro condition analysis. Combining the two types of data can ensure the scientific traffic management during the resumption period. From the conclusions of our study, the TAZs' average speed data can be used to understand the traffic operation state during the pandemic on a macro scale, but a further analysis regarding micro mechanisms and causality is still lacking. For example, the heterogeneity parts of the four clusters shows different fluctuation characteristics. However, based on the research presented in this paper, it is difficult to analyze the reasons or to support the formulation and implementation of relevant traffic policies.

Second, the transfer of travel modes is noteworthy. Although the

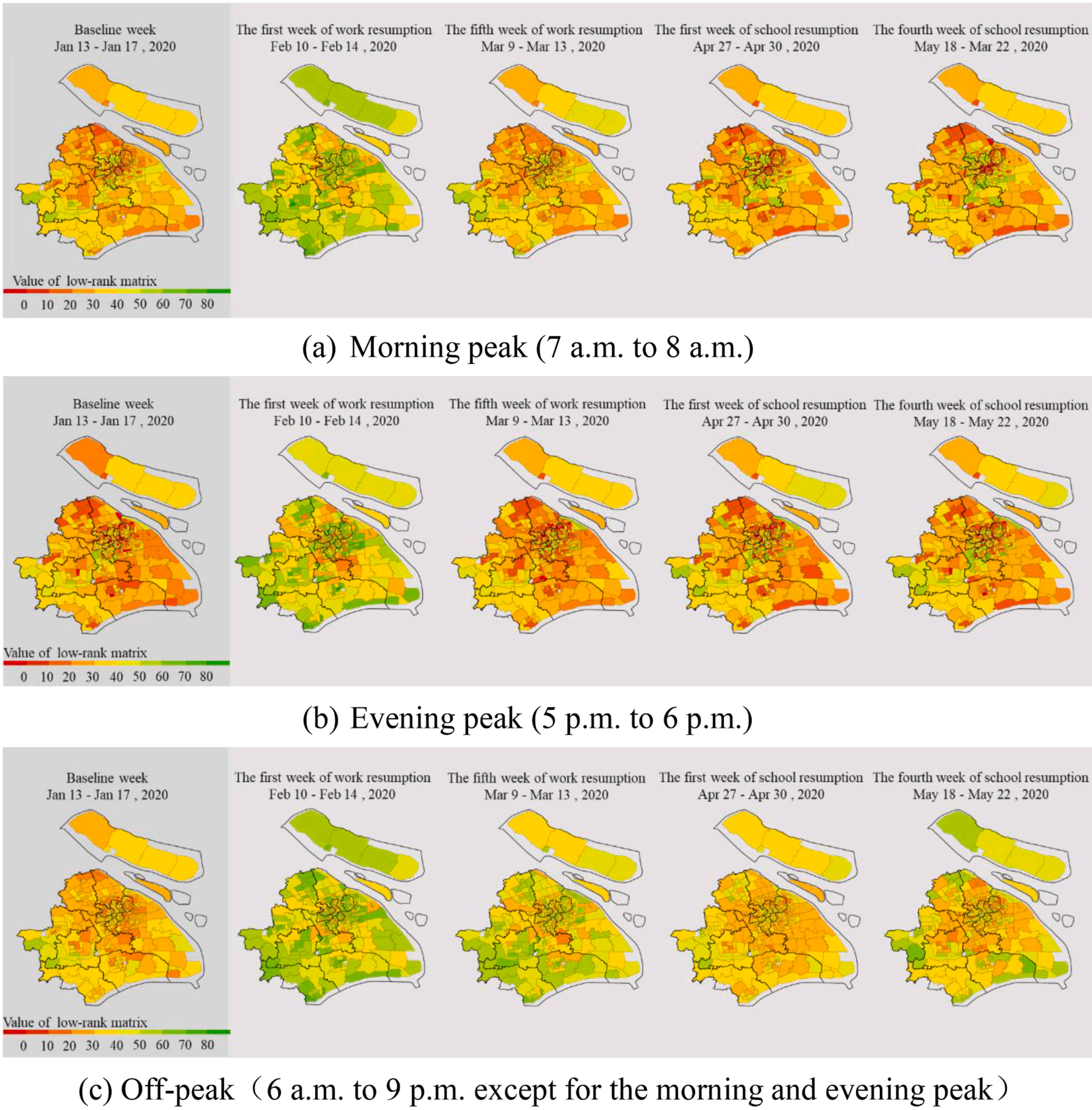


Fig. 7. Value of low-rank matrix of four stages in different period.

whole situation in Shanghai had been basically under control in late February, the ridership of public transport did not restore immediately due to the unresolved concern of pandemic. The proportion of private vehicles reached 32.6% in March 2020, an increase of 12.1% over March 2019[5](He et al., 2021; Wang et al., 2021). According to the results in this study, the traffic condition on working days had an even worsening trend compared with the pre-pandemic era in most TAZs. This may be resulted by the modal shift from public transport to private transport. As a megacity with a total population of more than 24 million, public transport must remain at the heart of urban mobility in Shanghai. While restrictions were being eased, measures should be taken to restore the public transport ridership. Firstly, passengers need protection and monitoring (Li et al., 2020). Timely sanitizing, face mask, temperature checks and travel history tracking are needed. Secondly, capacities should be increased to avoid crowding. Managing passenger flow, running more services and decreasing waiting times will help avoid crowding. Staggering work hours, encouraging working from home and other transport demand management will also help reduce peak demand. Thirdly, new solutions using smart technologies should be applied, which will be discussed in detail in the next section.

Third, information technology plays an increasingly important role in transportation during and after the pandemic. On the one hand, information technology makes the public transport system more informative, expanded and diversified. Mobile application should be developed to tell passengers that what time the bus will arrive or how crowded the bus is. In some areas significantly affected by the pandemic, such as TAZs in cluster 2, cluster 3 and cluster 4, public transport may function as a demand-responsive service and be more agile in its ability to transport people safely and quickly. On the other hand, information technology enables to understand the travel behavior patterns and

[5] Data from 2021 *Shanghai Comprehensive Transportation Development Annual Report* written by Shanghai Urban Rural Construction and Transportation Development Research Institute and Shanghai City Comprehensive Transportation Planning Institute

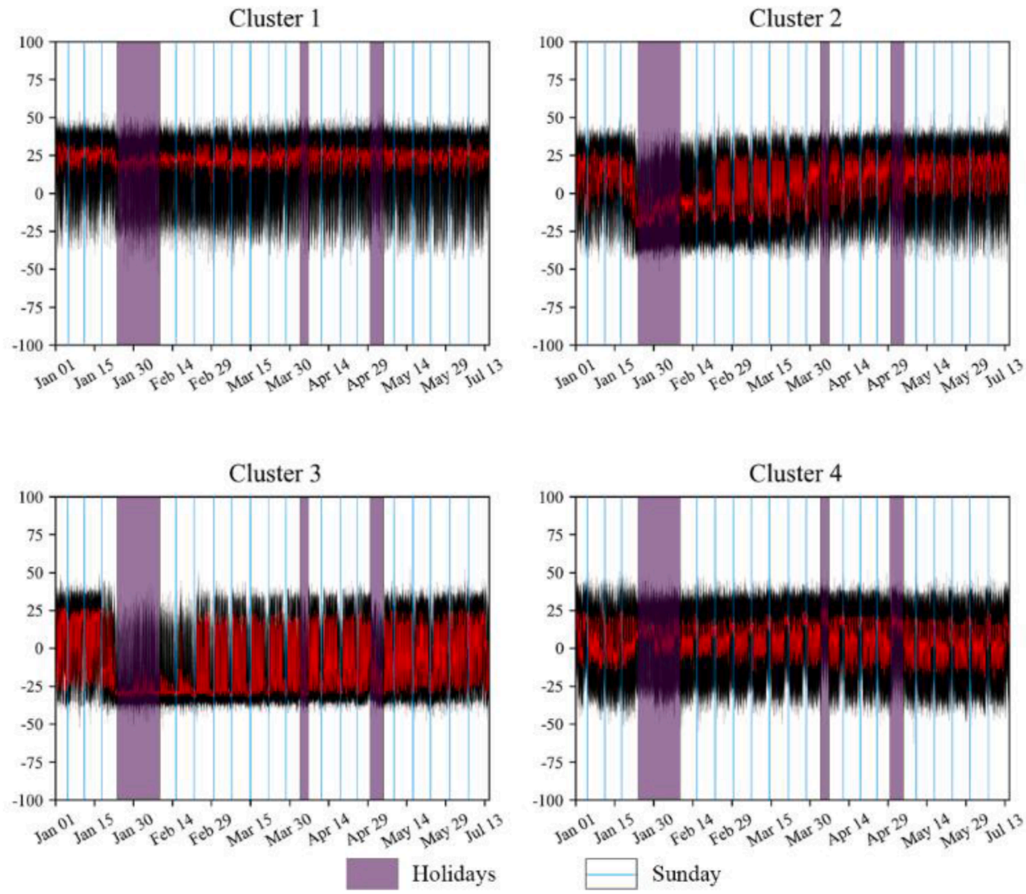


Fig. 8. Clustering result of row series of sparse matrix.

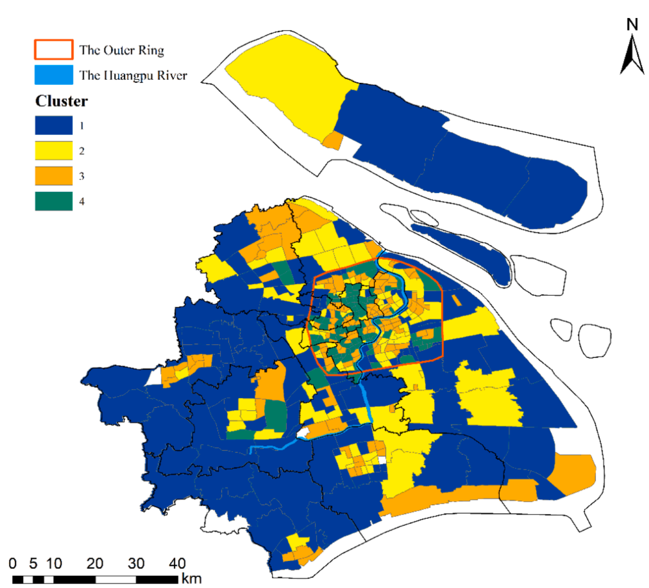


Fig. 9. Spatial distribution of clustering results.

supports the policy-making in the unprecedented public health challenge. For example, mobile phone data monitors the movement of high-risk population and helps evaluate the pandemic risk in the area (Gan et al., 2020). Baidu Migration Index provided by Baidu Map presents the trends of intercity human migration and intracity travel demand (He et al., 2020), and helps understand the inherent structure of human migration in the pandemic. The feasibility of demand-responsive transit and the clear understanding of travel behaviour patterns created a market space and momentum for MaaS (Mobility as a Service) service. In the pandemic era, MaaS gathers data to understand the unprecedented travel patterns and make journeys more efficient, and offers travelers mobility solutions based on their travel needs. Meanwhile, MaaS integrates multiple modes of transport, which improves transit network efficiency, decreases costs to the user, improves utilization of MaaS transit providers, and reduces city congestion.

Conclusions

In this study, an analytic framework was proposed to reveal the road spatiotemporal traffic evolution patterns during and after the COVID-19 pandemic. The proposed methodology included the separation of homogeneity and heterogeneity components from the overall traffic characteristics, TAZ classification based on the heterogeneous traffic characteristics, and the fluctuation analysis of heterogeneous characteristics. An empirical study of Shanghai was conducted to demonstrate the proposed methodology. The results showed that the proposed methodology could reveal the unevenly distributed impact of COVID-19 on the traffic congestion patterns. The results are summarized as below:

(i) Compared to the suburbs, the central areas are more affected by the travel restrictions during the pandemic. During the outbreak period, the traffic congestion was significantly alleviated in these TAZs. With the work and school resumption, the congestion recovered or even exceeded the level before the pandemic, while the state fluctuation of the outer suburbs in whole study periods is not obvious. Work resumption in different regions with different

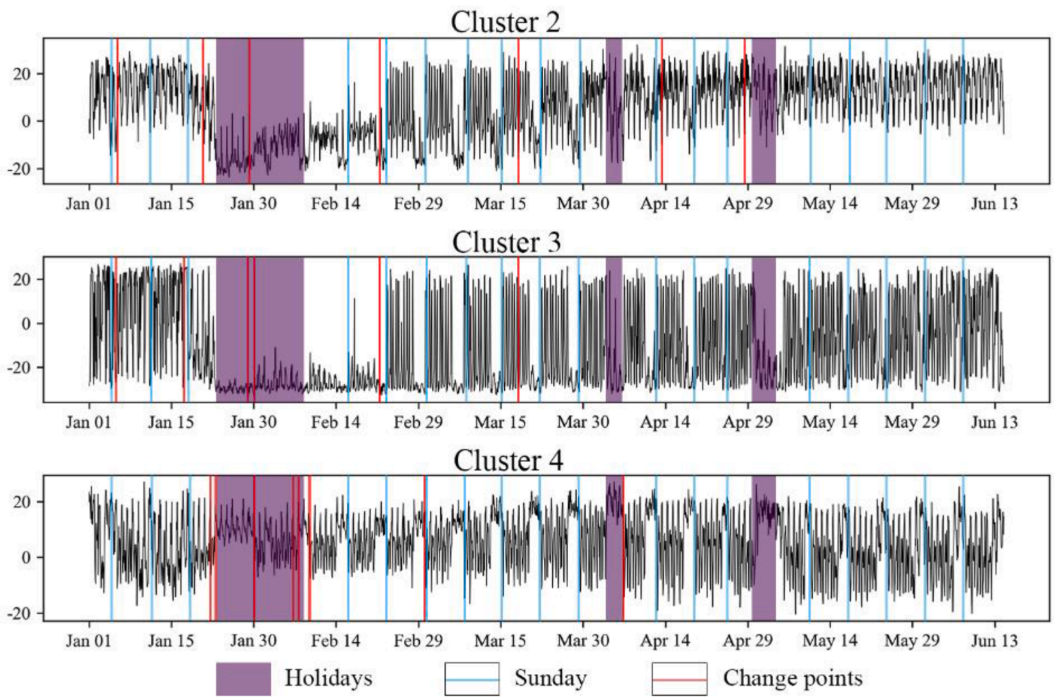


Fig. 10. Change points of each cluster center.

time is likely to be one of the reasons for the heterogeneity. The findings confirm some studies on mobility reduction in pandemic times to some degree (Borkowski et al., 2021; Chan et al., 2020; Wielechowski et al., 2020).

(ii) The traffic condition change process of different areas has common time nodes, but also have their own unique time nodes. In terms of quantity, there are fewer change points in the outer suburbs and more change points in the central areas. In terms of distribution, the change points in the central areas are concentrated around the Spring Festival and the outbreak of the pandemic.

(iii) Heterogeneity fluctuations show specific characteristics in different periods and areas. With the work resumption, working days congestion has an even worsening trend compared with the pre-pandemic level in most TAZs. The reasons may be related to the transfer of travel modes and the land use, which need to be further explored. The findings might make some supplements to the study of urban traffic congestion (Bao et al., 2017; Wen et al., 2014; Zhao and Hu, 2019).

This study proposed an approach to understand the urban roadway traffic changes in the complicated background of a pandemic. However, there are still some lacks for further improvement in future works. First, A travel behavior survey can be conducted to combine with macro condition monitoring data, the change in traffic congestion patterns can be further analyzed and interpreted. Second, based on regional land use and socio-economic data, a discrete choice or count data model can be established to explain the spatial distribution results more precisely. Third, we believe that an urban space activity observation system based on the multi-source data is the key to scientific management and control of human mobility during the pandemic. The system can monitor human mobility characteristics, and provide decision-making reference for more refined policy-making during the epidemic.

CRediT authorship contribution statement

Pengfei Xu: Formal analysis, Methodology, Writing – original draft. **Weifeng Li:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing. **Xianbiao Hu:** Writing – review & editing. **Hangbin Wu:** Writing – review & editing. **Jian Li:** Conceptualization, Writing – review & editing, Supervision.

Declaration of Competing 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.

Acknowledgement

This work was supported by the National Key R&D Program of China (No. 2018YFB1601100).

References

Anbaroğlu, B., Cheng, T., Heydecker, B., 2015. Non-recurrent traffic congestion detection on heterogeneous urban road networks. Transportmet. A: Transport Sci. 11 (9), 754–771.
Anbaroglu, B., Heydecker, B., Cheng, T., 2014. Spatio-temporal clustering for non-recurrent traffic congestion detection on urban road networks. Transport. Res. Part C: Emerg. Technol. 48, 47–65.
Arimura, M., Ha, T.V., Okumura, K., Asada, T., 2020. Changes in urban mobility in Sapporo city, Japan due to the Covid-19 emergency declarations. Transport. Res. Interdiscipl. Perspect. 7, 100212. https://doi.org/10.1016/j.trip.2020.100212.
Bao, Y., Xiao, F., Gao, Z., Gao, Z., 2017. Investigation of the traffic congestion during public holiday and the impact of the toll-exemption policy. Transport. Res. Part B: Methodol. 104, 58–81.
Beck, M.J., Hensher, D.A., Wei, E., 2020. Slowly coming out of COVID-19 restrictions in Australia: Implications for working from home and commuting trips by car and public transport. J. Transp. Geogr. 88, 102846. https://doi.org/10.1016/j.jtrangeo.2020.102846.
Borkowski, P., Jażdżewska-Gutta, M., Szmelter-Jarosz, A., 2021. Lockdowned: Everyday mobility changes in response to COVID-19. J. Transp. Geogr. 90, 102906. https://doi.org/10.1016/j.jtrangeo.2020.102906.
Brown, R.L., Durbin, J., Evans, J.M., 1975. Techniques for testing the constancy of regression relationships over time. J. Roy. Stat. Soc.: Ser. B (Methodol.) 37 (2), 149–163.
Candes, E.J., Plan, Y., 2010. Matrix completion with noise. Proc. IEEE 98 (6), 925–936.
Chan, H.F., Skali, A., Savage, D.A., Stadelmann, D., Torgler, B., 2020. Risk attitudes and human mobility during the COVID-19 pandemic. Sci. Rep. 10, 1–13.

Chen, C., Song, Y., Hu, X., Guardiola, I.G., Zhang, Y., 2020. Analysis of electric vehicle charging behavior patterns with function principal component analysis approach. J. Adv. Transport. 2020, 1–12. https://doi.org/10.1155/2020/8850654.

Chinazzi, M., Davis, J.T., Ajelli, M., Gioannini, C., Litvinova, M., Merler, S., Pastore y Piontti, A., Mu, K., Rossi, L., Sun, K., Viboud, C., Xiong, X., Yu, H., Halloran, M.E., Longini, I.M., Vespignani, A., 2020. The effect of travel restrictions on the spread of the 2019 novel coronavirus (COVID-19) outbreak. Science 368 (6489), 395–400.

de Haas, M., Faber, R., Hamersma, M., 2020. How COVID-19 and the Dutch 'intelligent lockdown' change activities, work and travel behaviour: Evidence from longitudinal data in the Netherlands. Transport. Res. Interdiscipl. Perspect. 6, 100150. https://doi.org/10.1016/j.trip.2020.100150.

Duan, Z., Lei, Z., Zhang, M., Li, H., Yang, D., 2018. Understanding multiple days' metro travel demand at aggregate level. IET Intel. Transport Syst. 13 (5), 756–763.

Engle, S., Stromme, J., Zhou, A., 2020. Staying at home: Mobility effects of COVID-19. SSRN Electron. J. https://doi.org/10.2139/ssrn.3565703.

Fatmi, M.R., 2020. COVID-19 impact on urban mobility. J. Urban Manage. 9 (3), 270–275.

Gan, T., Li, W., He, L., Li, J., 2020. Intracity pandemic risk evaluation using mobile phone data: The case of Shanghai during COVID-19. ISPRS Int. J. Geo-Inf. 9 (12), 715. https://doi.org/10.3390/ijgi9120715.

Gerbrands, J.J., 1981. On the relationships between SVD, KLT and PCA. Pattern Recogn. 14 (1-6), 375–381.

Güner, A.R., Murat, A., Chinnam, R.B., 2012. Dynamic routing under recurrent and non-recurrent congestion using real-time ITS information. Comput. Oper. Res. 39 (2), 358–373.

Hara, Y., Kuwahara, M., 2015. Traffic monitoring immediately after a major natural disaster as revealed by probe data–A case in Ishinomaki after the Great East Japan Earthquake. Transport. Res. Part A: Policy Pract. 75, 1–15.

He, L., Li, J., Sun, J., 2021. How to promote sustainable travel behavior in the post COVID-19 period: A perspective from customized bus services. Int. J. Transp. Sci. Technol. https://doi.org/10.1016/j.ijtst.2021.11.001.

He, L., Yu, Q., Li, W., Li, J., Yang, D., 2020. Inter-City Transportation Demand Under the COVID-19 Pandemic. Urban Transp. China 18, 51–61.

Hu, X., Yuan, Y., Zhu, X., Yang, H., Xie, K., 2019. Behavioral responses to pre-planned road capacity reduction based on smartphone GPS trajectory data: A functional data analysis approach. J. Intellig. Transport. Syst. 23 (2), 133–143.

Huang, J., Wang, H., Fan, M., Zhuo, A., Sun, Y., Li, Y., 2020. Understanding the impact of the COVID-19 pandemic on transportation-related behaviors with human mobility data. In: in: Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, pp. 3443–3450.

Inclan, C., Tiao, G.C., 1994. Use of cumulative sums of squares for retrospective detection of changes of variance. J. Am. Stat. Assoc. 89 (427), 913–923.

Jun, J., 2010. Understanding the variability of speed distributions under mixed traffic conditions caused by holiday traffic. Transport. Res. Part C: Emerg. Technol. 18 (4), 599–610.

Lakhina, A., Papagiannaki, K., Crovella, M., Diot, C., Kolaczyk, E.D., Taft, N., 2004. Structural analysis of network traffic flows, in: Proceedings of the Joint International Conference on Measurement and Modeling of Computer Systems. Association for Computing Machinery, New York, NY, USA, pp. 61–72. 10.1145/1005686.1005697.

Li, C.-S., Chen, M.-C., 2014. A data mining based approach for travel time prediction in freeway with non-recurrent congestion. Neurocomputing 133, 74–83.

Li, J., Chen, T., Zhang, Y., 2020. Research on Decision Support for Public Transport Operations and Management for Epidemic Prevention and Control of Infectious Diseases. China J. Highway Transp. 33, 30–42.

Li, J., Ozbay, K., Bartin, B., 2015. Effects of Hurricanes Irene and Sandy in New Jersey: traffic patterns and highway disruptions during evacuations. Nat. Hazards 78 (3), 2081–2107.

Li, J., Ozbay, K., Bartin, B., Iyer, S., Carnegie, J.A., 2013. Empirical evacuation response curve during hurricane irene in cape may county, new jersey. Transp. Res. Rec. 2376 (1), 1–10. https://doi.org/10.3141/2376-01.

Li, J., Xiang, T., He, L., 2021a. Modeling epidemic spread in transportation networks: A review. J. Traffic Transport. Eng. 8 (2), 139–152. https://doi.org/10.1016/j.jtte.2020.10.003.

Li, J., Xu, P., Li, W., 2021b. Urban road congestion patterns under the COVID-19 pandemic: A case study in Shanghai. Int. J. Transp. Sci. Technol. 10 (2), 212–222. https://doi.org/10.1016/j.ijtst.2021.03.001.

Liu, Z., Sharma, S., 2006. Statistical investigations of statutory holiday effects on traffic volumes. Transp. Res. Rec. 1945 (1), 40–48.

Lowcock, E.C., Rosella, L.C., Foisy, J., McGeer, A., Crowcroft, N., 2012. The social determinants of health and pandemic H1N1 2009 influenza severity. Am. J. Public Health 102 (8), e51–e58.

Murray-Tuite, P., Wolshon, B., 2013. Evacuation transportation modeling: An overview of research, development, and practice. Transport. Res. Part C: Emerg. Technol. 27, 25–45.

Neuburger, L., Egger, R., 2020. Travel risk perception and travel behaviour during the COVID-19 pandemic 2020: A case study of the DACH region. Curr. Issues Tour. 24 (7), 1003–1016.

Nian, G., Peng, B., Sun, D., Ma, W., Peng, B., Huang, T., 2020. Impact of COVID-19 on urban mobility during post-epidemic period in megacities: From the perspectives of taxi travel and social vitality. Sustainability 12 (19), 7954. https://doi.org/10.3390/su12197954.

Oum, T.H., Wang, K., 2020. Socially optimal lockdown and travel restrictions for fighting communicable virus including COVID-19. Transp. Policy 96, 94–100.

Polson, N.G., Sokolov, V.O., 2017. Deep learning for short-term traffic flow prediction. Transport. Res. Part C: Emerg. Technol. 79, 1–17.

Skabardonis, A., Varaiya, P., Petty, K.F., 2003. Measuring recurrent and nonrecurrent traffic congestion. Transp. Res. Rec. 1856 (1), 118–124.

Ullah, S., Finch, C.F., 2013. Applications of functional data analysis: A systematic review. BMC Med. Res. Method. 13, 43.

Wang, X., Li, J., Bian, R., Zhou, Y., 2021. Commuting behavior changes in post-Pandemic period: A case study of Shanghai during COVID-19. Presented at the Transportation Research Board 100th Annual Meeting, Washington, DC., USA.

Wang, Z., Hu, K., Xu, K., Yin, B., Dong, X., 2012. Structural analysis of network traffic matrix via relaxed principal component pursuit. Comput. Netw. 56 (7), 2049–2067.

Wen, H., Sun, J., Zhang, X., 2014. Study on traffic congestion patterns of large city in China taking Beijing as an example. Proced. –Soc. Behav. Sci. 138, 482–491.

Wielechowski, M., Czech, K., Grzęda, Ł., 2020. Decline in Mobility: Public Transport in Poland in the time of the COVID-19 Pandemic. Economies 8 (4), 78.

Wolshon, B., McArdle, B., 2009. Temporospatial analysis of Hurricane Katrina regional evacuation traffic patterns. J. Infrastruct. Syst. 15 (1), 12–20.

Xiao, H., Tian, H., Zhao, J., Zhang, X., Li, Y., Liu, Y., Liu, R., Chen, T., 2011. Influenza A (H1N1) transmission by road traffic between cities and towns. Chin. Sci. Bull. 56 (24), 2613–2620.

Xu, B., Tian, H., Sabel, C., Xu, B., 2019. Impacts of road traffic network and socioeconomic factors on the diffusion of 2009 pandemic Influenza A (H1N1) in mainland China. Int. J. Environ. Res. Public Health 16 (7), 1223. https://doi.org/10.3390/ijerph16071223.

Xu, X., Wang, S., Dong, J., Shen, Z., Xu, S., Xue, B., 2020. An analysis of the domestic resumption of social production and life under the COVID-19 epidemic. PLoS ONE 15 (7), e0236387. https://doi.org/10.1371/journal.pone.0236387.

Yoneyama, T., Das, S., Krishnamoorthy, M., 2010. A hybrid model for disease spread and an application to the SARS pandemic. Jasss 15. 10.18564/jasss.1782.

Zhao, J., Gao, Y., Bai, Z., Wang, H., Lu, S., 2019. Traffic speed prediction under non-recurrent congestion: Based on LSTM method and BeiDou navigation satellite system data. IEEE Intell. Transp. Syst. Mag. 11 (2), 70–81.

Zhao, P., Hu, H., 2019. Geographical patterns of traffic congestion in growing megacities: Big data analytics from Beijing. Cities 92, 164–174.

Zhou, Z., Li, X., Wright, J., Candes, E., Ma, Y., 2010. Stable principal component pursuit, in: 2010 IEEE International Symposium on Information Theory. IEEE, pp. 1518–1522.