



Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.



Quantifying human mobility resilience to the COVID-19 pandemic: A case study of Beijing, China

Yaxi Liu^{a,b}, Xi Wang^{a,b}, Ci Song^{a,b}, Jie Chen^a, Hua Shu^a, Mingbo Wu^{a,b}, Sihui Guo^{a,b}, Qiang Huang^{a,b}, Tao Pei^{a,b,c,*}

^a State Key Laboratory of Resources and Environmental Information System, Institute of Geographical Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China

^b University of Chinese Academy of Sciences, Beijing 100049, China

^c Jiangsu Center for Collaborative Innovation in Geographical Information Resource Development and Application, Nanjing 210023, China

ARTICLE INFO

Keywords:

Human mobility
Resilience
COVID-19
Pandemic
Heterogeneities
Mobile phone data

ABSTRACT

Human mobility, as a fundamental requirement of everyday life, has been most directly impacted during the COVID-19 pandemic. Existing studies have revealed its ensuing changes. However, its resilience, which is defined as people's ability to resist such impact and maintain their normal mobility, still remains unclear. Such resilience reveals people's response capabilities to the pandemic and quantifying it can help us better understand the interplay between them. Herein, we introduced an integrated framework to quantify the resilience of human mobility to COVID-19 based on its change process. Taking Beijing as a case study, the resilience of different mobility characteristics among different population groups, and under different waves of COVID-19, were compared. Overall, the mobility range and diversity were found to be less resilient than decisions on whether to move. Females consistently exhibited lower resilience than males; middle-aged people exhibited the lowest resilience under the first wave of COVID-19 while older adult's resilience became the lowest during the COVID-19 rebound. With the refinement of pandemic-control measures, human mobility resilience was enhanced. These findings reveal heterogeneities and variations in people's response capabilities to the pandemic, which can help formulate targeted and flexible policies, and thereby promote sustainable and resilient urban management.

1. Introduction

Mobility, a basic form of human behavior associated with working, shopping, education, traveling, and other social and economic activities in everyday life, has been most directly impacted during the COVID-19 pandemic. Based on various mobility tracing data, previous studies have revealed the ensuing changes in human mobility across multiple regions (Lee et al., 2020; Pan et al., 2020; Tan et al., 2021; Beria & Lunkar, 2021). However, the ability of people to resist such impact and maintain their normal mobility, which we define as human mobility resilience (Wang & Taylor, 2014, 2016; Roy et al., 2019), remains unclear. Different from mobility changes, such resilience reveals the impact of COVID-19 from the perspective of people's responses. Quantifying it can help us better understand the interplay between human mobility and the pandemic, so as to support sustainable and resilient urban management in areas such as resource allocation (Zhou et al., 2021), policy making

(Rao et al., 2021) and urban planning (Sharifi & Khavarian-Garmsir, 2020). For example, different people may present different response capabilities to the pandemic (Weill et al., 2020; Zhang et al., 2021; Flor et al., 2022), therefore, quantifying mobility resilience of different population and revealing its group heterogeneities can help city managers quickly identify people who are more vulnerable to the pandemic and thereby conduct targeted resource allocations to avoid the problem of social inequality (Van Dorn et al., 2020; Blundell et al., 2020; Flor et al., 2022); different pandemic control measures may bring different degrees of impact on human mobility (Wang et al., 2020; Czech et al., 2021; Huang et al., 2022), therefore, quantifying human mobility resilience under different pandemic control measures and detecting its variations can help policy makers formulate more reasonable measures to enhance human mobility resilience and thereby minimize the negative impact of the pandemic (Bonaccorsi et al., 2020; Škare et al., 2021; Mueller et al., 2021). Moreover, as COVID-19 continues and people

* Corresponding authors at: State Key Laboratory of Resources and Environmental Information System, Institute of Geographical Sciences and Natural Resources Research, Chinese Academy of Sciences, 11A, Datun Road, Chaoyang District, Beijing 100101, China.

E-mail address: peit@reis.ac.cn (T. Pei).

<https://doi.org/10.1016/j.scs.2022.104314>

Received 14 August 2022; Received in revised form 18 October 2022; Accepted 19 November 2022

Available online 20 November 2022

2210-6707/© 2022 Elsevier Ltd. All rights reserved.

begin to realize that they might have to live with it (Batty, 2022), how to coordinate pandemic prevention and control with normal social and economic development is becoming a matter of concern (Iftekhhar et al., 2021; Eyawo et al., 2021; Coccia, 2022). Therefore, it is becoming increasingly necessary to study human mobility resilience.

The COVID-19 pandemic has boosted unprecedented research to understand the interplay between human mobility and pandemics (Benita, 2021; Alessandretti, 2022; Zhang et al., 2022), while most of them only focused on the changes in human mobility during the initial stage of COVID-19. The results generally demonstrate that the non-pharmacological intervention measures during this stage reduced intensity of human mobility (Lee et al., 2020; Yabe et al., 2020; Pan et al., 2020; Gibbs et al., 2020; Benita 2021). Although a few studies have revealed that this reduction varies across different regions (Bonaccorsi et al., 2020; Carella et al., 2022; Lee et al., 2020; Galeazzi et al., 2021) and among different population groups (Pullano et al., 2020; Zhang et al., 2021; Weill et al., 2020; Jay et al., 2020), which actually implies different resilience capabilities in response to COVID-19, a quantitative assessment of such resilience is still absent.

Recently, Lu et al. (2022) proposed the concept of regional mobility resilience and quantified it by comparing the number of passenger arrivals at each city with that in the preceding year and explored its relationship with regional culture. They found that regional mobility resilience exhibits spatial autocorrelation and heterogeneity; the mobility in areas with high levels of cultural tightness is less affected by COVID-19. Mu et al. (2022) measured the resilience of inter-city mobility through the network analysis perspective. By analyzing mobility networks in the Beijing–Tianjin–Hebei urban agglomeration, they found that core cities with high development levels are more vulnerable to COVID-19 than marginal cities. While these studies exploratively introduced the resilience perspective into human mobility analysis in the context of COVID-19, certain problems still exist. First, they only focused on the resilience of inter-city mobility and its regional differences, however, the resilience of detailed intra-city mobility and its disparities among different population groups were not revealed. Second, the resilience assessment was based on a direct comparison of mobility indicators before and during COVID-19, however, the change process of human mobility over different stages of COVID-19 was not considered.

To overcome the above problems, Wang et al. (2022) defined travel behavior resilience to investigate how intra-city public transport use varied and recovered during COVID-19 and compared it among different population groups. Taking Kunming, China as a case study, they found that intra-city public transport use recovered slowly after being affected by the pandemic and the travel behavior resilience differs by groups. Commuters present greater resilience, while the elderly show lesser resilience. However, there are still some limitations of this study. First, they only focused on the subway mobility of frequent travelers, which accounts for a small proportion of mobility in a city. The mobility of infrequent travelers and those who commute using other types of transportation modes were not included. Second, only the first wave of COVID-19 was considered. The resilience of human mobility during subsequent waves of COVID-19, which most cities have experienced, remains unknown.

Through this study, which was inspired by the resilience assessment in the context of natural disasters (for a review, see the “Related works” section), we attempted to comprehensively quantify the resilience of human intra-city mobility to COVID-19 based on its change process. To achieve this, three contributions have been made. First, the fine-grained and long-term mobile phone signaling data, which cover people traveling by different modes of transportation, were used to track the complete change process of human mobility over different COVID-19 phases. Second, an integrated resilience assessment framework, which combines the evaluation of resilience capabilities during different pandemic phases, was proposed to quantify human mobility resilience more accurately. Third, based on the quantification of human mobility

resilience, a comparison from three dimensions was conducted to: (1) better understand the impact of COVID-19 on different aspects of human mobility by comparing the resilience of different mobility characteristics; (2) reveal group heterogeneities in people’s response capabilities to the pandemic by comparing the mobility resilience of people with different gender and age attributes; (3) track the variations in people’s response capabilities to the pandemic over different phases by comparing human mobility resilience in face of different waves of COVID-19 outbreaks.

2. Related works

The term resilience is first introduced by Holling (1973) in ecology to measure the capability of ecosystems to absorb change and disturbance and still maintain their initial states. Since then, this notion has been extensively used in multiple disciplines ranging from environmental research to urban science, engineering, psychology, sociology, and economics (Bruneau et al., 2003; Bhamra et al., 2011; Meerow et al., 2016; Schwarz, 2018). Its general definition can be described as the ability of a system to resist the effects of a disruptive shock and to return to its initial states (Nan & Sansavini, 2017; da Mata Martins et al., 2019). Following this general definition, the human mobility resilience can be defined as the ability of people to resist the impacts caused by a public crisis and to maintain their normal mobility behavior (Wang & Taylor, 2014, 2015, 2016; Roy et al., 2019; Zhang et al., 2019). Here the public crises include natural disasters such as hurricanes or earthquakes, disease outbreaks such as the COVID-19 pandemic, and other events that may disrupt human mobility. Among them, the human mobility resilience to natural disasters has been extensively studied. The assessment of human mobility resilience generally consists of two parts: measurement of human mobility and frameworks for resilience assessment. In the following, we will review the related works from these two aspects respectively.

2.1. Measurement of human mobility

Measuring human mobility, namely quantifying the characteristics of people’s movement behavior based on their trajectories, is the prerequisite of assessing human mobility resilience (Zhang et al., 2019). As a foundational work, this issue has been extensively studied in multiple disciplines and several metrics have been proposed to measure human mobility from different perspectives (Gonzalez et al., 2008; Song et al., 2010; Xia et al., 2018; Kishore et al., 2020; Xu et al., 2021). These metrics can be broadly divided into three categories. The first category measures the intensity of mobility, which includes the ratio of moved people measuring the overall mobility intensity of a region and the number of visited places or the movement frequency measuring the individual mobility intensity of a person (Xu et al., 2016; Xu et al., 2018; Xi et al., 2020). The second category measures the spatial patterns of mobility, which includes the movement displacement measuring the distance between two consecutive visited locations, the radius of gyration measuring the spatial extent of a person’s movement, and the total movement distance measuring the overall travel distance of a person (Gonzalez et al., 2008; Song et al., 2010; Xu et al., 2016). The third category measures the diversity of mobility, which includes the mobility entropy measuring the diversity of movement directions and activity entropy measuring the diversity of visited places (Pappalardo et al., 2016; Xu et al., 2018, 2021).

Despite the above abundant measurements of human mobility, the mobility characteristics considered in assessing human mobility resilience were still limited. The most widely used metrics in existing studies to assess human mobility resilience is the movement displacement (Wang & Taylor, 2014, 2015, 2016; Roy et al., 2019; Zhang et al., 2019), followed by the radius of gyration (Wang & Taylor, 2014, 2015, 2016). These two metrics can only unilaterally indicate the spatial pattern of human mobility, while the resilience of other aspects of human mobility

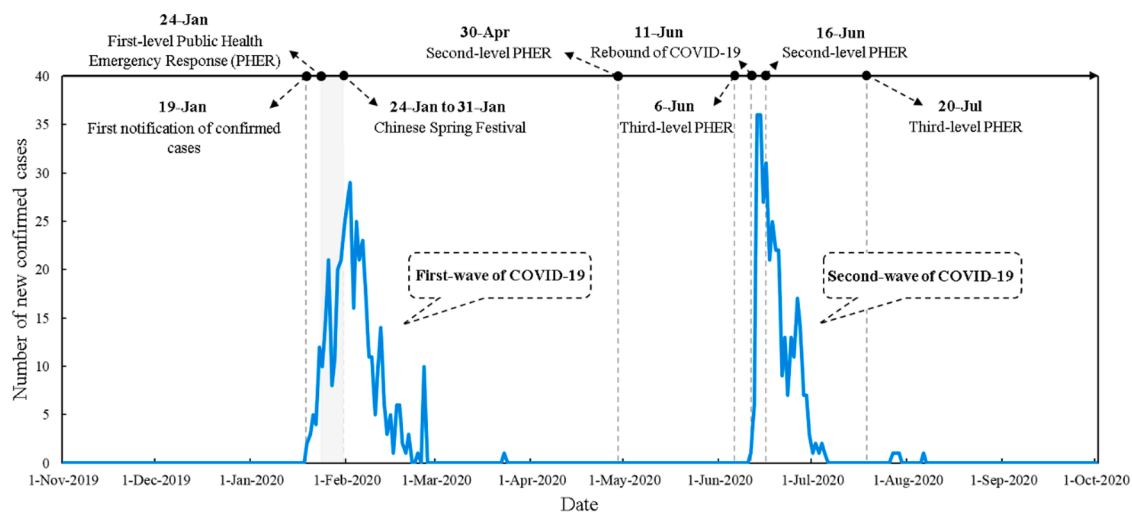


Fig. 1. The daily number of new cases and timeline of city responses over the first two waves of COVID-19 outbreaks in Beijing.

still remains unknown.

2.2. Frameworks for resilience assessment

According to the frameworks used for assessing resilience, the related works can be divided into two categories. The first category estimate human mobility resilience by directly comparing the perturbed mobility pattern during a disaster to their normal patterns. For example, based on geo-tagged Twitter data, Wang and Taylor (2014, 2015, 2016) analyzed human mobility perturbations under multiple types of natural disasters (e.g., hurricane, earthquake, winter storm, etc.) and made a comparison with their normal patterns. The results demonstrate that even though human mobility experienced significant perturbations during these disasters, it exhibited high resilience: the movement displacement still followed a power-law distribution as normal; the center of movements and radius of gyration were correlated to their values in the normal state. However, such assessment of human mobility resilience is qualitative and not necessarily accurate, because the human mobility perturbation is usually highly dynamic and changing over the development of the disaster.

To overcome this problem, the second category estimate human mobility resilience based on the concept of the resilience triangle (Bruneau et al., 2003; Hosseini et al., 2016), which refers to the complete change process of human mobility during a disaster. For example, Zhang et al. (2019) proposed a metric to measure the accumulated perturbation (AP) of human mobility over the entire timespan of an extreme weather event. The value of AP is determined not only by the magnitude of mobility perturbation, but also by the duration of impacts caused by the event. Similarly, Roy et al. (2019) proposed a method to estimate human mobility resilience by constructing the change curve of human mobility over time. The area under this curve from being disrupted to recovering is calculated to measure the resilience of human mobility in response to an extreme event. Such assessment of resilience considered the temporal characteristics of human mobility perturbation. However, the metrics used can only reflect the overall resilience capability, the resilience capability during different phases such as absorptive capability to reduce the negative impacts, adaptive capability to adapt to the event and restorative capability to recover to the normal, can not be reflected (Nan & Sansavini, 2017).

2.3. Gaps in assessing human mobility resilience

In summary, although existing studies about human mobility resilience have made substantial progress, some problems still exist. First, most of them focused on the human mobility resilience to natural

disasters, while that to disease outbreaks such as the COVID-19 pandemic has received little attention. Second, the metrics used to measure human mobility characteristics were not comprehensive enough. Third, the frameworks used for assessing resilience fail to integrate the resilience capabilities over different phases.

To fill up these gaps, our study attempted to investigate human mobility resilience to the COVID-19 pandemic. As compared to the existing studies, we stand to contribute to the related works in two ways. First, unlike previous research that only used the movement displacement or the radius of gyration as measurements of human mobility, we considered the potential impact of COVID-19 on different aspects of human mobility and introduced five indicators to measure it from a multi-dimensional viewpoint. Second, in contrast with previous studies that only considered the instantaneous or overall human mobility perturbation when assessing resilience, we proposed an integrated assessment framework to assess the resilience of human mobility by comprehensively considering its change process from disruption to recovery, and finally reaching a new steady state.

3. Study area and data

3.1. Study area

Beijing, the capital city of China, with a total population of over 21 million people, was selected in this research to conduct a case study due to two reasons. First, it is a typical large city in which the rapid spread of COVID-19 occurred and the daily life of citizens was greatly affected. Second, as the absolute political center of China, Beijing implemented the most rapid, precise and strict pandemic prevention and control measures, which have always been an example for other cities to follow. Therefore, quantifying its citizens' mobility change and resilience under COVID-19 can also serve as a useful reference to other cities.

Since the first case of COVID-19 was reported on January 19, 2020 in Beijing, a total of 2958 cases, including 2100 local cases and 858 cases imported from overseas, have been confirmed as of August, 2022 (Beijing Municipal Health Commission, 2022). During this period, Beijing repeatedly experienced several waves of COVID-19 outbreaks. Here we chose the first wave of outbreak at the beginning of 2020 and the second wave of outbreak in mid-2020 to conduct our research, because the former can reflect the situation of the first shock of pandemic while the latter can be regarded as a typical representative of subsequent pandemic rebound. Meanwhile, to track the complete change process of human mobility before, during and after each outbreak, we finally selected 10 months (from December 2019 to September 2020) as our study period. Fig. 1 shows the daily number of new cases and the

Table 1
Description of the original mobile phone signaling data.

Fields	Description	Example
User ID	Encrypted identifier for each user	07d471***95bf92
Tower ID	The mobile phone tower that a user was located	14,756
Lon	Longitude of the mobile phone tower	116.5***2
Lat	Latitude of the mobile phone tower	39.7***3
T	The time stamp when a location was recorded	2020-03-02 00:00:24

timeline of city responses over this period. The first wave of outbreak lasted 48 days (from January 19 to March 6) and a total of 420 confirmed cases were reported; the second wave of outbreak lasted 26 days (from June 11 to July 6) and a total of 335 confirmed cases were reported. The change of Public Health Emergency Response (PHER) from the first to the third level indicates the relaxation of pandemic prevention and control measures implemented by the government.

3.2. Data

The data we used in this research were anonymized mobile phone signaling data collected from one of the three communication operators in China, which continuously collect the location information of mobile phone users by recording the signal connection relationship between mobile phones and phone towers. Table 1 shows the detailed description of the dataset. Note that the user ID has been fully encrypted to protect personal privacy so that no individual person can be identified or associated with any external information. Based on this dataset, the mobility behavior of each mobile phone user can be extracted (Gonzalez et al., 2008; Hoteit et al., 2014; Li et al., 2019; Kishore et al., 2020; Song et al., 2020).

In addition to user location information, the gender and age attributes of each user were also collected. According to the gender attribute, we divided users into two groups: males and females. According to the age attribute, we divided users into four groups by considering their social status (Wang et al., 2019): group 1 (age ≤ 24 years), group 2 (25 years ≤ age ≤ 39 years), group 3 (40 years ≤ age ≤ 59 years), and group 4 (60 years ≤ age). Among them, users aged under 24 years mainly

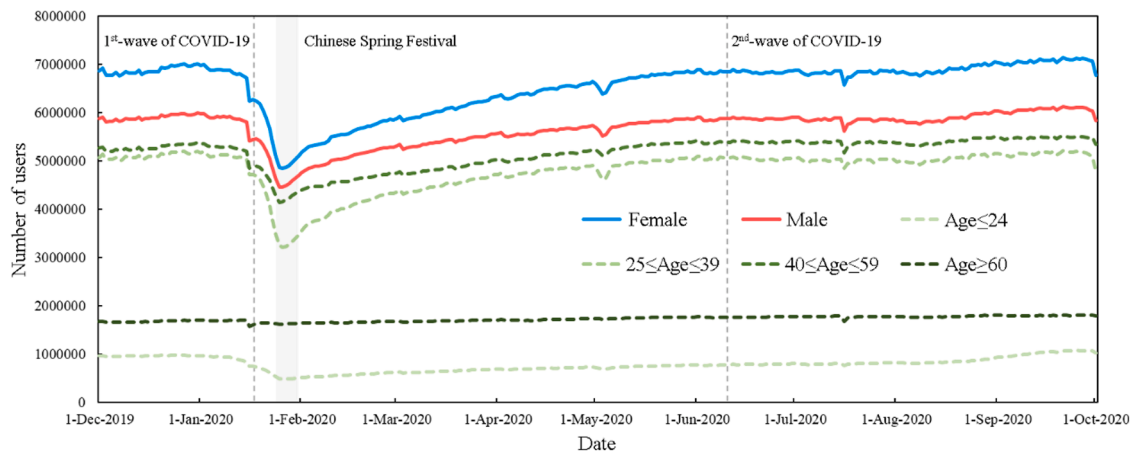


Fig. 2. Changes in the number of mobile phone users with different attributes over our study period.

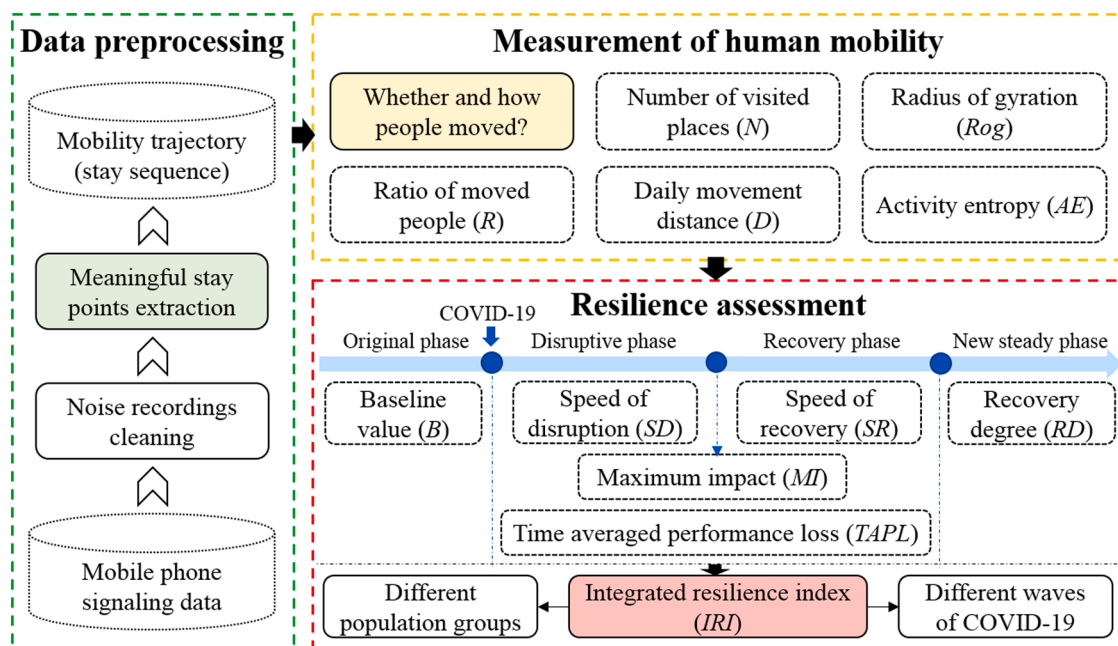


Fig. 3. The flowchart of the analytical framework.

Table 2
Rule-based approach for noise recordings cleaning and meaningful stay points extraction.

Recording types	Data characteristics	Detecting index	Detecting rules
Drift recordings	Jumping from one tower to another at a very high speed	The speed of two consecutive location recordings (S_0)	If $S_0 > 120$ km/h, we determined that a signal drift had occurred, and the recordings was deleted
Oscillation recordings	Exhibiting a clustering pattern among several adjacent phone towers	The distance of two consecutive location recordings (D_0)	If $D_0 < 500$ m, we determined that a signal oscillation had occurred, and the recordings were merged into a cluster as candidate stay points
Meaningful stay points	The duration time is enough to carry out common human activities	The duration of a cluster of candidate stay points (T_0)	If $T_0 > 30$ min, we assumed that it was a meaningful stay and the centroid of the cluster was calculated to represent the final stay point

Note: 120 km/h is the maximum speed limit allowed on the roads in Beijing; 500 m is the average distance between two adjacent phone towers in our dataset; 30 min is usually the shortest duration of a common human activity (e.g., in-home, working, schooling, etc.).

represent the early adulthood people who are still in school; users aged 25 to 39 years mainly represent young adults who have just started working and may not yet have a family; users aged 40 to 59 years mainly represent middle-aged adults who have been working for a long time and have had a family; users aged over 60 years mainly represent older adults who have retired from work.

The changes in the number of users with different attributes over our study period are shown in Fig. 2, from which we can see that the number of each group of users decreased after the outbreak of COVID-19 and then gradually increased. On average, there were over 12 million users on each day, accounting for more than 60% of the population in the city. The decrease in the number of users is mainly caused by the departure of some people who returned back to their hometown cities when the Chinese Spring Festival came. In this study, we mainly focused on the intra-city mobility of people who stayed in Beijing. Considering that the intra-city mobility characteristics of these reduced users before leaving Beijing are not significantly different from that of other users, this part of the reduced users does not affect our final analysis results significantly.

4. Methodology

The methodological framework can be roughly divided into three parts (Fig. 3). First, the data preprocessing was conducted to remove noise recordings and further extract meaningful mobility trajectory of each user. Subsequently, based on the extracted trajectory, five mobility indicators were introduced to comprehensively measure different aspects of human mobility. Finally, an integrated resilience assessment framework was applied to quantify the resilience of different mobility characteristics by analyzing the change process of different mobility indicators.

4.1. Data preprocessing

Based on mobile phone signaling data, the original movement trajectory of a user can be extracted by ordering the location recordings by time stamp, which can be expressed as follows:

$$\text{Trj} = \{(x_1, y_1, t_1), (x_2, y_2, t_2), \dots, (x_i, y_i, t_i), \dots, (x_n, y_n, t_n)\} \quad (1)$$

where x_i and y_i are projected coordinates of the i -th location of a user recorded at time t_i ; n is the total number of location recordings of a user. However, one issue worth noting is that there might be some noise in the original trajectories. Specifically, the location recordings are dependent on the phone towers that the mobile phones were connected to, which might oscillate back and forth between nearby towers due to workload balancing, or suddenly drift to distant towers in a short time period due to signal drifts (Csáji et al., 2013; Zhao et al., 2018; Yang et al., 2019b). To address this issue, we proposed a rule-based approach (see Table 2 for details) to delete drift and oscillation recordings and further extract meaningful stay points that each user actually visited, referring to existing studies (Tu et al., 2017; Yang et al., 2019b; Yin et al., 2021; Xu et al., 2021).

In doing so, the original movement trajectory of each user was transformed into a sequence of meaningful stay points as follows:

$$\text{Trj} = s_1 \rightarrow s_2 \rightarrow s_3 \rightarrow \dots \rightarrow s_i \rightarrow \dots \rightarrow s_n \quad (2)$$

$$s_i = (cx_i, cy_i, dur_i) \quad (i = 1, 2, \dots, n) \quad (3)$$

where s_i is the i -th stay point of a user; n is the total number of stay points; cx_i and cy_i are the centroid coordinates of the i -th stay point; dur_i is the duration time at the i -th stay point.

4.2. Measurement of human mobility

Based on the users' extracted stay sequences, as set out in Section 4.1, several indicators were introduced in this section to measure human mobility. Generally, the impact of a pandemic on human mobility is manifested in two aspects: on the one hand, the pandemic prevention and control measures might restrict people's movement (Peak et al., 2018; Tian et al., 2020a; Zhou et al., 2020), and on the other hand, people's willingness to travel might be reduced due to fear of the pandemic (Chen et al., 2020; Mu et al., 2021; Wang et al., 2022). Therefore, we characterized human mobility patterns around two issues:

- (1) Did people move?
- (2) If they moved, what were their mobility characteristics?

Regarding the first issue, we introduced an indicator named the ratio of moved people (R) as a measurement. This indicator is the relative ratio between the number of moved people and total number of people investigated. The formula can be expressed as follows:

$$R = \frac{P_{moved}}{P} \quad (4)$$

where P_{moved} is the number of people moved; P is the total number of people investigated. This indicator reflects the willingness of people to engage in movement (Xi et al., 2020; Liu et al., 2021a). A larger value of R indicates that more people decided to move.

Regarding the second issue, we focused on moved people and further introduced four indicators to quantify their mobility characteristics. The first indicator was the number of visited places (N), which is the number of unique stay points that a moved person visited (Xu et al., 2016, 2018, 2021). Given a person's stay sequence as formula (2), this indicator can be calculated as follows:

$$N = |\text{set}(s_1, s_2, s_3, \dots, s_n)| \quad (5)$$

where $\text{set}(\cdot)$ is a function to remove the duplicated elements in a sequence. A large value of N indicates that the person not only engages in a movement, but also visits more places.

The second indicator was the radius of gyration (Rog), which has been widely used in existing research to quantify the spatial range of a

person’s movement (Gonzalez et al., 2008; Song et al., 2010; Xu et al., 2016, 2018, 2021). It is the root mean squared distance between stay points and their center of mass and can be calculated as follows:

$$Rog = \sqrt{\frac{1}{n} \sum_{i=1}^n ((cx_i - \bar{x})^2 + (cy_i - \bar{y})^2)} \quad (6)$$

$$(\bar{x}, \bar{y}) = \left(\frac{1}{n} \sum_{i=1}^n cx_i, \frac{1}{n} \sum_{i=1}^n cy_i \right) \quad (7)$$

where (\bar{x}, \bar{y}) is the center of mass of a person’s stay points. A large value of *Rog* suggests a large movement range of the person.

The third indicator was daily movement distance (*D*), which is the sum of the Euclidean distance between each pair of consecutive stay points and can be calculated as follows (Calabrese et al., 2013; Kishore et al., 2020):

$$D = \sum_{i=1}^{n-1} \sqrt{(cx_i - cx_{i+1})^2 + (cy_i - cy_{i+1})^2} \quad (8)$$

This indicator measures the overall travel distance of a person and can be regarded as a complement to *Rog*. A large value of *D* indicates a long movement distance of the person. The units of indicators *Rog* and *D* were all converted to kilometers.

The fourth indicator was activity entropy (*AE*), which has been widely used in research to quantify the diversity of a person’s mobility (Pappalardo et al., 2016; Xu et al., 2018, 2021). Inspired by the diversity evaluation of biotopes in landscape ecology (Gobattoni et al., 2011; Turner & Gardner, 2015; Assumma et al., 2021), this indicator is defined as the Shannon entropy of a person’s stay points and can be calculated as follows:

$$AE = - \sum_{i=1}^n p(s_j) \log(p(s_j)) \quad (9)$$

$$p(s_j) = \frac{dur_j}{\sum_{j=1}^N dur_j} \quad (10)$$

where s_j is the *j*-th unique stay points of a person; dur_j is the stay duration at point s_j ; $p(s_j)$ denotes the proportion of duration at the unique stay point s_j . In contrast with the number of visited places, *AE* considers the duration of stay in each place and can reflect the person’s preferences to different places. A large value of *AE* indicates that the diversity of a person’s mobility is high. For example, a person visits three places (residential place, work place, and shopping mall) a day before a pandemic and the duration time for each visit is 11 hours, 9 hours, and 4 hours, respectively. During the pandemic, this person’s visited places are not changed but the duration time for each visit changes to 19 hours, 4 hours, and 1 hours, respectively. Therefore, the activity entropy of this person before the pandemic ($AE = -\frac{11}{24} \times \log(\frac{11}{24}) - \frac{9}{24} \times \log(\frac{9}{24}) - \frac{4}{24} \times \log(\frac{4}{24}) = 1.024$) is larger than that during the pandemic ($AE = -\frac{19}{24} \times \log(\frac{19}{24}) - \frac{4}{24} \times \log(\frac{4}{24}) - \frac{1}{24} \times \log(\frac{1}{24}) = 0.616$), indicating the mobility before the pandemic is more diverse.

All these mobility indicators were calculated on a daily scale and for each indicator, the average value for the entire city and different population groups were calculated. Then, we ordered the daily average value of mobility indicators by date to form several time series, which indicated the change process of human mobility over different stages of the pandemic. By analyzing such time series, the resilience of human mobility to the pandemic could be assessed from two perspectives: at the city level and of different population groups.

4.3. Framework for resilience assessment

In this study, we employed an integrated framework originally

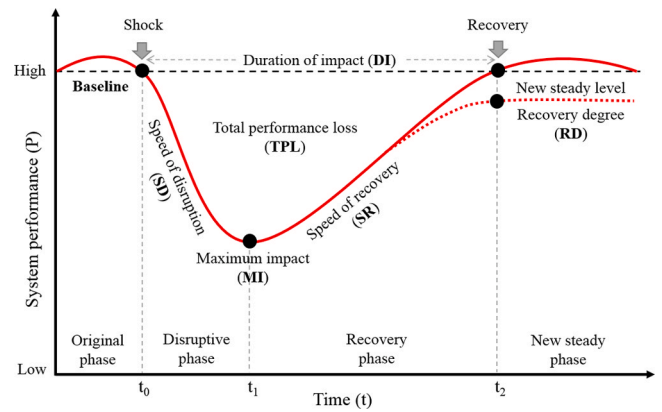


Fig. 4. Conceptual depiction of the integrated framework for assessing resilience of a system.

developed by Nan and Sansavini (2017) to quantify human mobility resilience. Fig. 4 provides a conceptual depiction of this framework to quantify the resilience of a system, where the y-axis represents the measurement of system performance (*P*) and the red curve (known as the resilience curve) represents the change of system performance in face of a disruptive shock. According to the change patterns of system performance, the x-axis (*Time*) can be divided into four phases, and six detailed metrics were introduced to quantify the system’s resilience capability during different phases. Note that the x-axis (*Time*) here can be on any scale and in our study, the resilience curve was conducted on a daily scale.

The first phase is the original phase before the shock ($Time < t_0$), in which the system performance is at a normal level. The average value of system performance during this phase was calculated as a baseline to represent the pre-shock state of the system.

The second phase is the disruptive phase ($t_0 \leq Time \leq t_1$), in which the system performance starts to drop due to the disruption of shock and finally reaches the lowest level. During this phase, the speed of disruption (*SD*), which is defined as the average slope of the system performance’s drop, was introduced to account for the ability of the system to absorb the impact. Meanwhile, the maximum impact (*MI*), which is defined as the difference between the baseline level and the lowest level that the system performance reaches, was introduced to account for the strength of the system to resist disruption. A low speed of disruption and small maximum impact indicate a high resilience of the system.

The third phase is the recovery phase ($t_1 \leq Time \leq t_2$), in which the system performance starts to increase and finally reaches a new steady level. During this phase, the speed of recovery (*SR*), which is defined as the average slope of the system performance’s increase, was introduced to account for the ability of the system to adapt to the shock and restore to normal. A high speed of recovery indicates a high resilience of the system.

The fourth phase is the new steady phase ($Time > t_2$), in which the system performance reaches a new steady level. It must be noted that this new steady level may be the same as the original level, or be higher or lower than the original level. Therefore, the recovery degree (*RD*), which is defined as the ratio between the new steady level and original steady level (*Baseline*), was introduced to account for the final extent of the recovery. A high value of recovery degree indicates a high resilience of the system.

In addition to the above four metrics, two metrics, which have been widely used in existing research to evaluate the overall impact of the shock (Bruneau et al., 2003; Kontokosta & Malik, 2018; Roy et al., 2019; Hong et al., 2021) were also included. The first was the total performance loss (*TPL*) of the system, which is defined as the area between the system performance curve and the baseline. The second was the duration of impact (*DI*), which is defined as the sum of the duration of

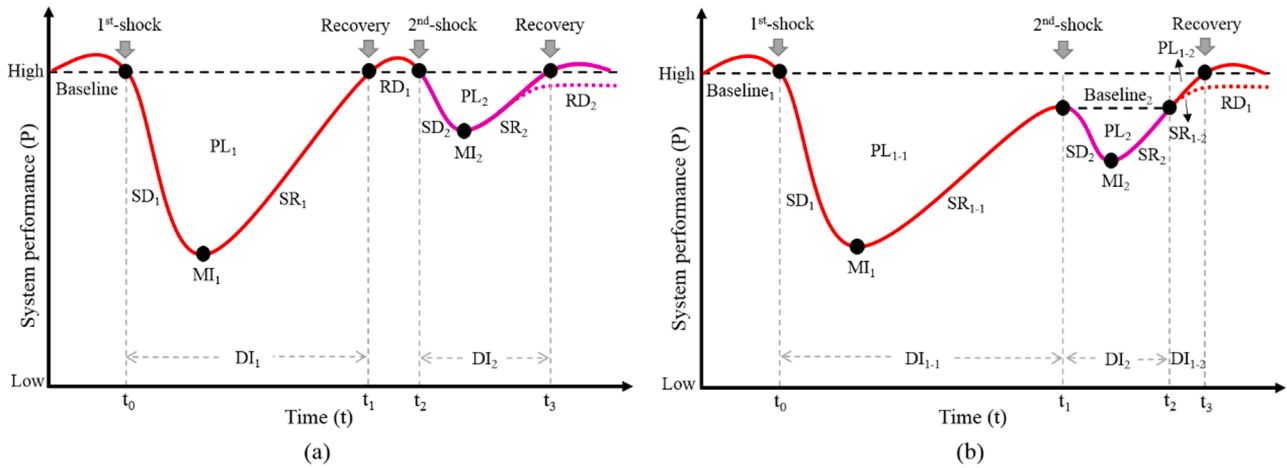


Fig. 5. Different scenarios in assessing the resilience of a system to pandemic shocks, where curves in different colors represent system performance changes caused by different waves of a pandemic. (a) The impact of the two waves of the pandemic are independent; (b) The impact of the two waves of the pandemic are overlaid.

disruption and recovery. Based on these two metrics, a new metric named the time averaged performance loss (TAPL) was calculated as follows:

$$TAPL = \frac{TPL}{DI} = \frac{\int_{t_0}^{t_2} (Baseline - P(t))dt}{t_2 - t_0} \quad (11)$$

where t_0 represents the time when the system performance starts to drop and t_2 represents the time when the system performance reaches a new steady level. As stated by Nan and Sansavini (2017), this metric “provides a time-independent indication of both adaptive and restorative capabilities as responses to the disruptive events.” The smaller value of TAPL, the more resilient a system.

Finally, from an overall perspective, an integrated resilience index (IRI), which combines the evaluation of resilience over different phases, was proposed. Considering that the resilience of a system is positively correlated with speed of recovery and recovery degree, while negatively correlated with speed of disruption, maximum impact, and the time averaged performance loss, this integrated resilience index can be expressed as follows:

$$IRI = (Baseline - MI) * \frac{SR}{SD} * TAPL^{-1} * RD \quad (12)$$

This framework comprehensively considers the complete change process of system performance, so that all resilience capabilities can be included. When applying this framework to pandemic shock, one issue

that should be noted is that the outbreak of a pandemic usually recurs in waves. A system may not completely recover from the disruption of a previous wave of outbreak while the next wave of outbreak starts. Therefore, in this paper, we proposed to assess the resilience under different waves of a pandemic separately by decomposing the system performance curve. Taking two waves of a pandemic as an example, Fig. 5 presents different scenarios that need to be considered. In Fig. 5(a), the shocks in two waves of the pandemic were independent so that the resilience to each shock could be assessed directly. In Fig. 5(b), the recovery phase after the first shock was interrupted by the second shock, and therefore, before assessing the resilience to the first shock, the system performance change caused by the second shock was required to be decomposed out first. The resilience metrics that needed to be calculated for each different wave of shocks are labeled in the corresponding positions in Fig. 5.

In this study, the system performance corresponded to five mobility indicators introduced in Section 4.2. Each indicator represents one aspect of human mobility characteristics and its change process forms one resilience curve. Based on different resilience curves, the resilience of different mobility characteristics can be assessed. To facilitate the comparison of resilience between different mobility characteristics, the relative value of each mobility indicator compared to its corresponding pre-pandemic baseline value was used to construct the resilience curve. Considering that the outbreak of the first wave of COVID-19 in Beijing (January 19, 2020) was proximate to the Chinese Spring Festival (January 25, 2020), we calculated the average value of mobility

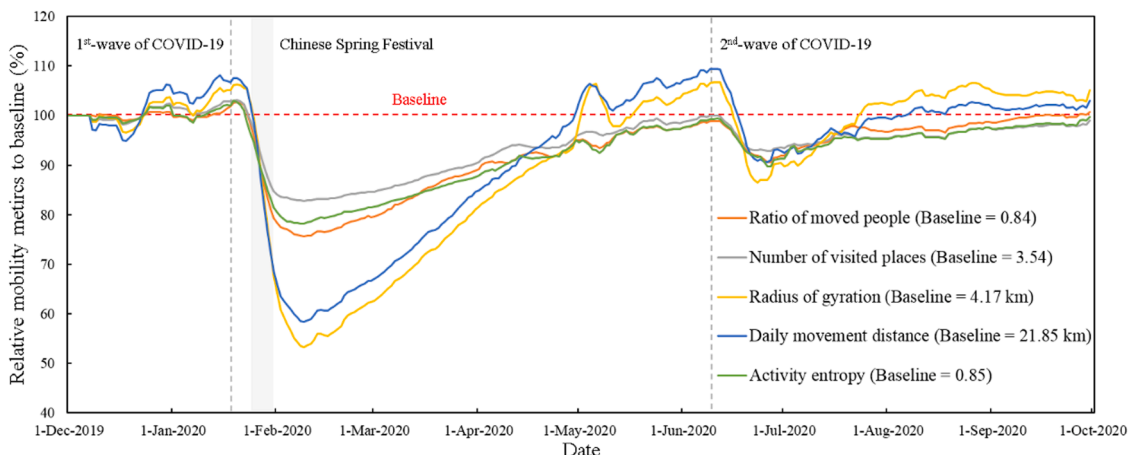


Fig. 6. Resilience curves of human mobility to COVID-19 at city level.

Table 3
Detailed resilience metrics of human mobility to different waves of COVID-19 at city level.

	The first wave of COVID-19					The second wave of COVID-19				
	R	N	Rog	D	AE	R	N	Rog	D	AE
Speed of disruption	1.47	1.06	3.09	2.75	1.27	0.55	0.48	1.92	1.10	0.60
Maximum impact (%)	24.40	17.21	46.76	41.70	21.80	8.27	7.14	15.39	9.90	9.57
Speed of recovery	0.19	0.14	0.58	0.53	0.17	0.12	0.06	0.45	0.23	0.10
Recovery degree	1.00	1.00	1.00	1.00	0.99	1.00	0.99	1.00	1.00	1.00
Duration of impact (d)	150	140	100	98	141	87	112	40	52	112
Total performance loss	16.15	12.12	25.67	22.10	15.62	3.40	4.29	2.75	2.19	4.70

Note: R, N, Rog, D, and AE denote ratio of moved people, number of visited places, radius of gyration, daily movement distance, and activity entropy.

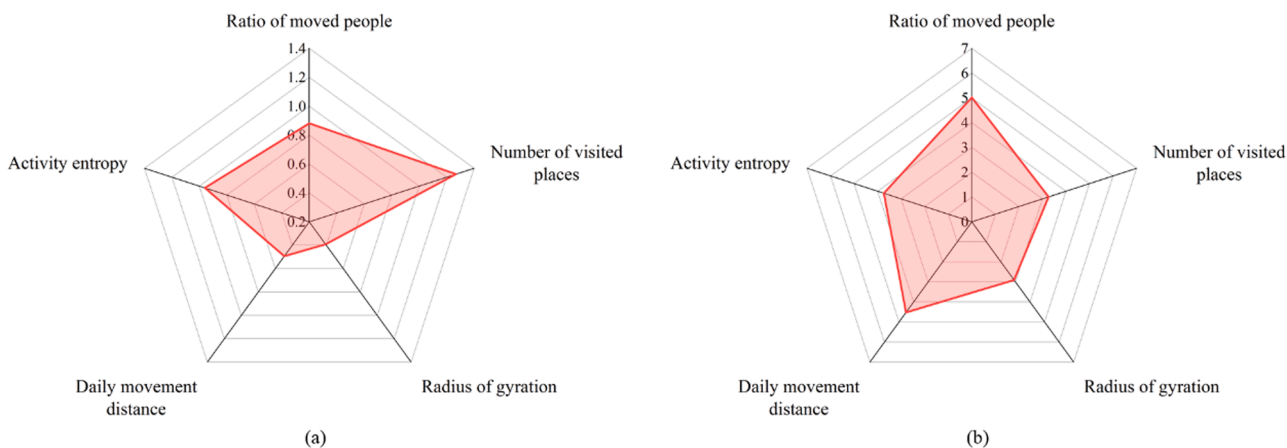


Fig. 7. Integrated resilience index of human mobility at city level. (a) The first wave of COVID-19; (b) The second wave of COVID-19.

indicators during December 2019 as the baseline value to avoid the potential impact of the Chinese Spring Festival on human normal mobility. Based on the constructed resilience curves, the resilience assessment framework introduced above was applied.

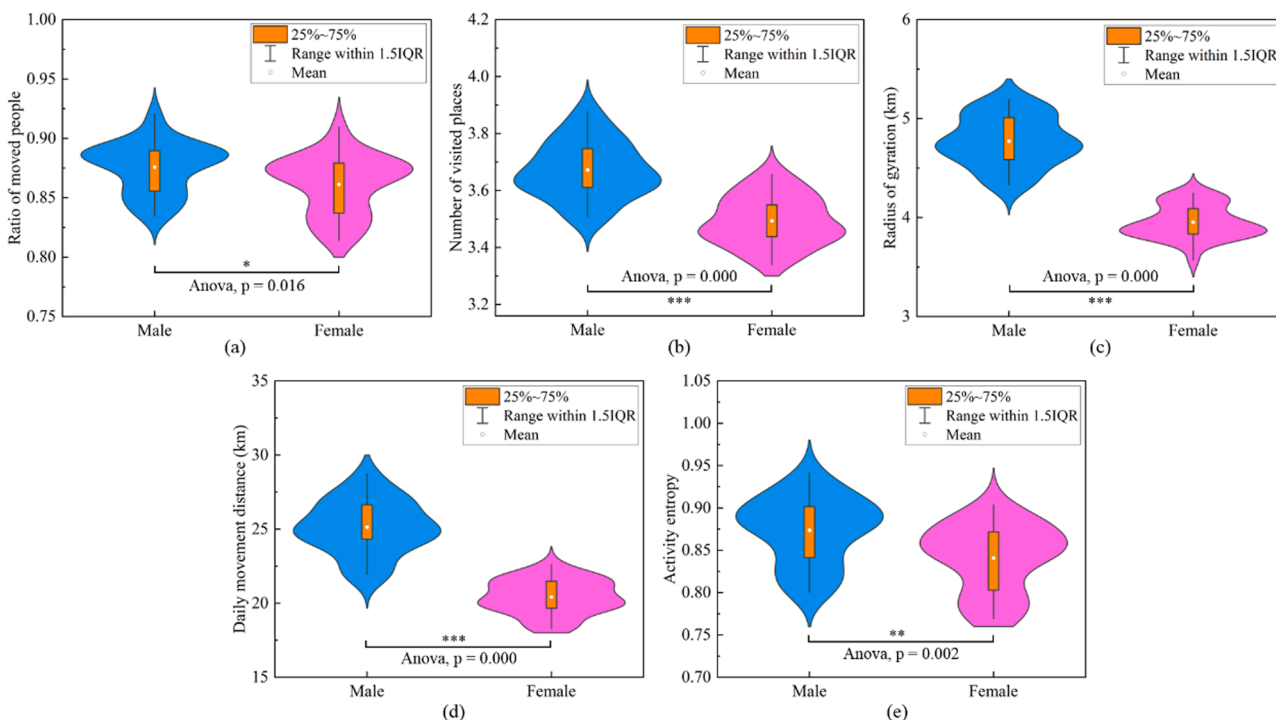


Fig. 8. Baseline values of mobility indicators for people with different genders. (a) Ratio of moved people; (b) Number of visited places; (c) Radius of gyration; (d) Daily movement distance; (e) Activity entropy.

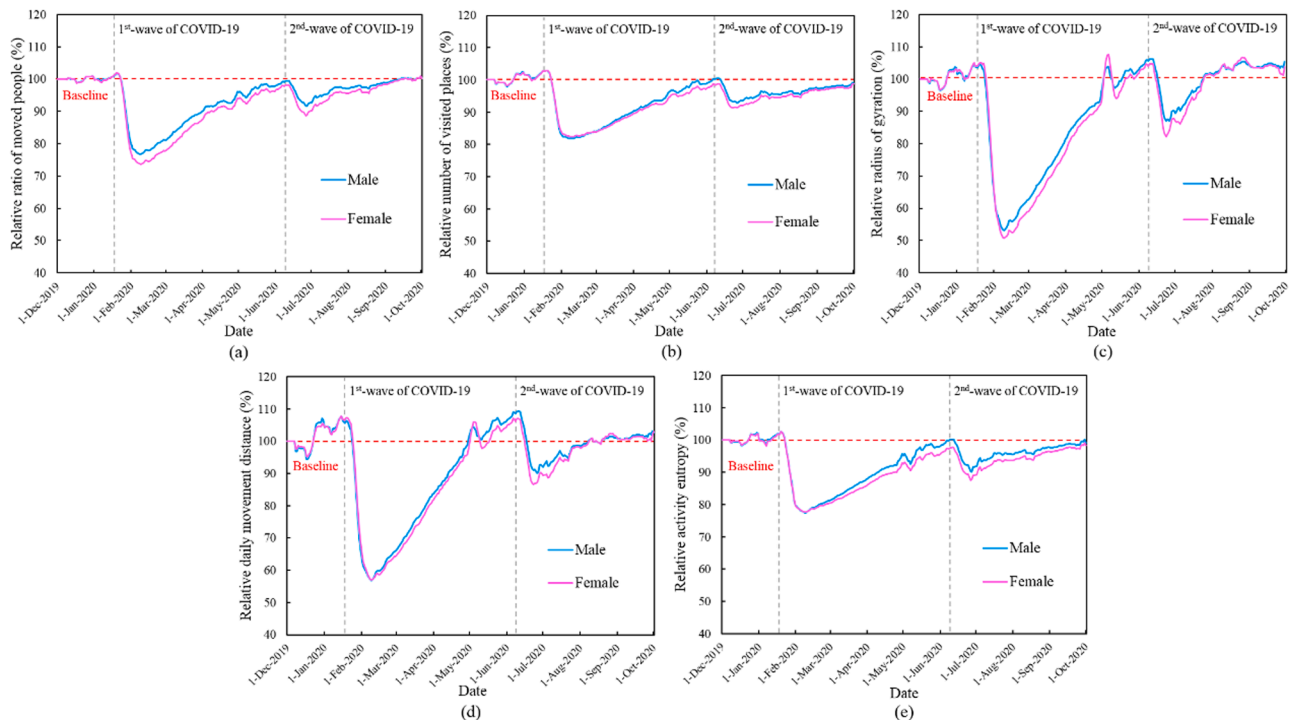


Fig. 9. Resilience curves of human mobility to COVID-19 for people with different genders. (a) Ratio of moved people; (b) Number of visited places; (c) Radius of gyration; (d) Daily movement distance; (e) Activity entropy.

5. Results

5.1. Human mobility resilience at city level

The resilience curves of human mobility to COVID-19 at the city level are shown in Fig. 6, where different mobility indicators are represented by different colors and the baseline value of each indicator is illustrated in the legend. Before the outbreak of COVID-19, all the indicators fluctuated around their baseline values and then increased gradually due to the approach of the Chinese Spring Festival. However, as the first wave of COVID-19 broke out, they decreased rapidly and reached their lowest level around February 9, 2020. Subsequently, as the COVID-19 gradually came under control, they gradually recovered. By the time of the second wave of the COVID-19 outbreak, the radius of gyration, daily movement distance, and number of visited places had returned to their normal levels while the other two indicators had not. The rebound of COVID-19 caused a similar pattern of changes in human mobility as that caused by the first wave of the outbreak, but the extent and the duration of change were less. Comparison of different indicators shows that even though different mobility characteristics show similar overall change patterns, their resilience capabilities during different phases are different.

To further reveal these differences, the detailed resilience metrics extracted during different phases are shown in Table 3. We observed that irrespective of the first or the second wave of COVID-19, the radius of gyration and daily movement distance exhibited high speed of disruption and large maximum impact but high speed of recovery and short duration of impact. The other three indicators exhibited relatively low speed of disruption and small maximum impact but low speed of recovery and long duration of impact.

Based on the detailed resilience metrics, the integrated resilience index of human mobility at the city level are shown in Fig. 7, where the five dimensions of the radar chart represent the value of resilience indexes for five mobility indicators. During the first wave of COVID-19, the number of visited places showed the strongest resilience, followed by the activity entropy and ratio of moved people. The resilience of the

radius of gyration and daily movement distance were the lowest. During the second wave of COVID-19, the ratio of moved people showed the highest resilience, followed by the daily movement distance and activity entropy. The resilience of the number of visited places and radius of gyration were the lowest. It is worth noting that the resilience index of all indicators for the second wave of COVID-19 was larger than that for the first wave of COVID-19, indicating the enhancement of human mobility resilience with the development of COVID-19.

5.2. Human mobility resilience of different population groups

Existing studies have revealed that people with different demographic attributes (i.e., gender and age) usually show different mobility patterns (Lenormand et al., 2015; Luo et al., 2016; Yang et al., 2019a; Gauvin et al., 2020; Olivieri & Fageda, 2021). In face of the pandemic outbreak, how did their mobility patterns change? Are there disparities in their mobility resilience to the pandemic? To answer these questions, we compared the mobility resilience of people with different genders and in different age groups in this section.

5.2.1. People with different genders

First, the pre-pandemic baseline values of mobility indicators for people with different genders are shown in Fig. 8, where the analysis of variance (ANOVA) was used to test the significance of their differences. For all indicators, the values of males are larger than that of females. Meanwhile, the p-values of the ANOVA are all smaller than 0.05, indicating that the differences are significant.

Compared to baseline values, the resilience curves of human mobility to COVID-19 for people with different genders are shown in Fig. 9. We observed that the extent of the impact caused by COVID-19 on females was larger than that on males, which indicates that the outbreak of the pandemic reinforced the gender differences in the mobility pattern. Specifically, when the first wave of COVID-19 broke out, its maximum impact on the ratio of moved people and the radius of gyration of females (26.31% and 49.24%) was larger than that of males (23.33% and 46.95%). Regarding the number of visited places, daily

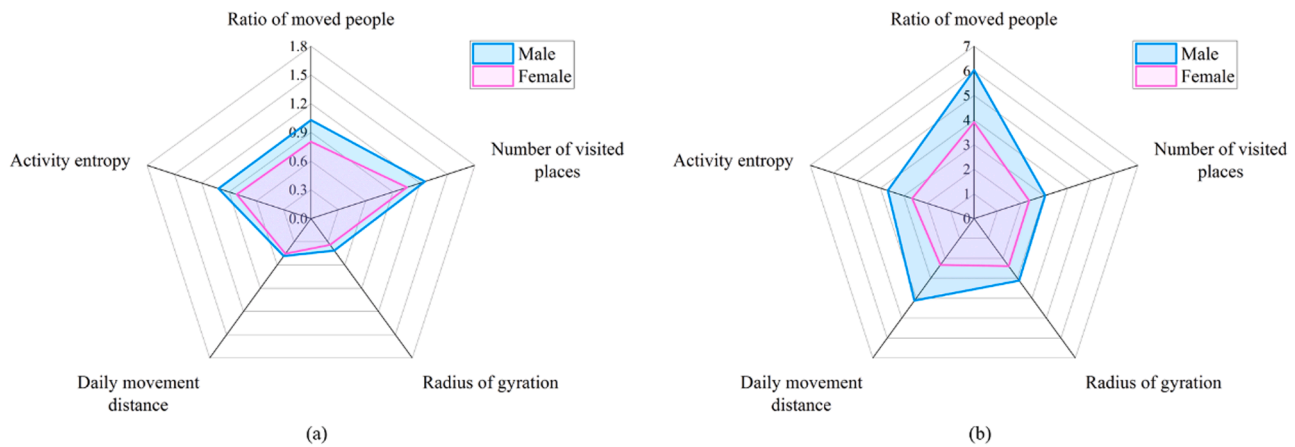


Fig. 10. Integrated resilience index of human mobility for people with different genders. (a) The first wave of COVID-19; (b) The second wave of COVID-19.

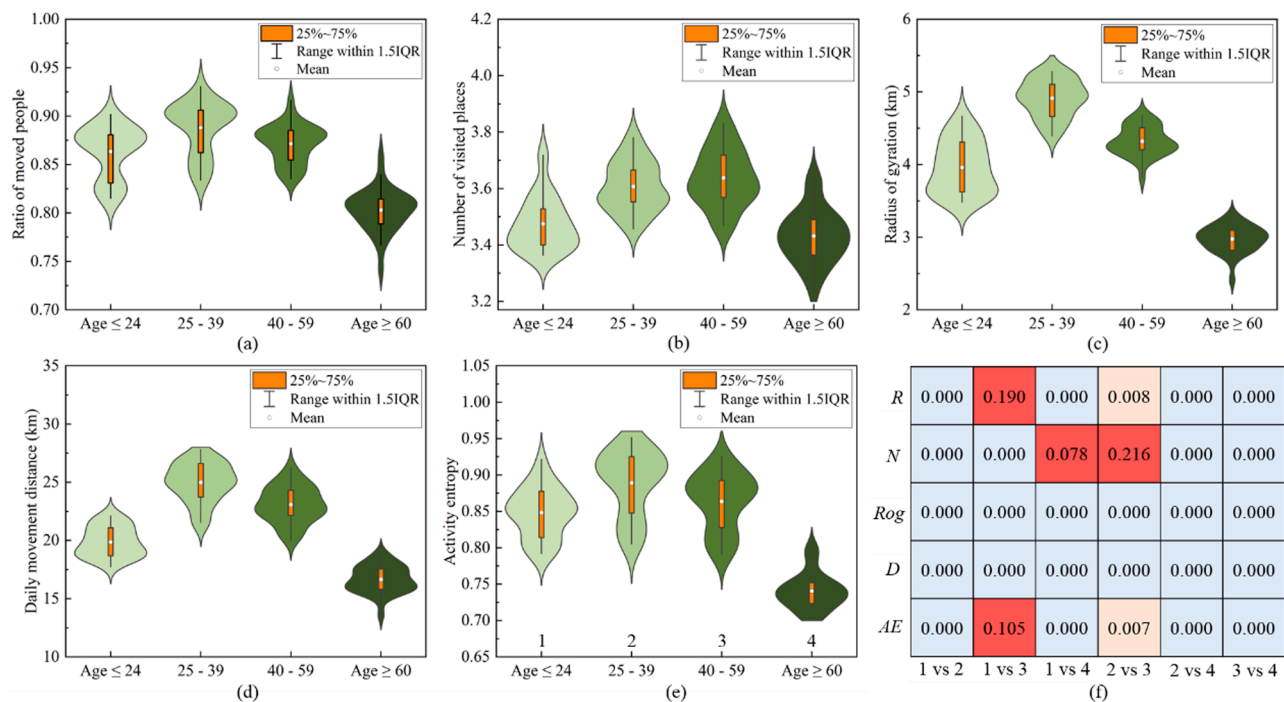


Fig. 11. Baseline values of human mobility for people in different age groups and the results of significant difference test by analysis of variance. (a) Ratio of moved people; (b) Number of visited places; (c) Radius of gyration; (d) Daily movement distance; (e) Activity entropy; (f) Significance (p-value of ANOVA test) of differences between any two groups of population.

movement distance, and activity entropy, even though they suffered a similar impact for females and males, the recovery speed of females (0.14, 0.53, and 0.16) was relatively smaller than that of males (0.16, 0.54, and 0.19). When the second wave of COVID-19 broke out, its maximum impact on all indicators for females was larger than that for males. The detailed comparisons can be seen in the calculation results of the detailed mobility resilience metrics for females and males as shown in Appendix Table A1.

Based on the detailed resilience metrics, the integrated resilience index of human mobility for people with different genders are shown in Fig. 10. Irrespective of the first or the second wave of COVID-19, the resilience index of all mobility indicators for males was larger than that for females. This indicates that females are more vulnerable to the pandemic shock. Moreover, with the enhancement of human mobility resilience from the first to the second wave of COVID-19, the differences between males and females have also been reinforced. In face of the first wave of COVID-19, the average value of five mobility indicators’

resilience index for males was 0.84 and that for females was 0.69. In face of the second wave of COVID-19, the average value of five mobility indicators’ resilience index for males was 4.00 and that for females was 2.73.

5.2.2. People in different age groups

The pre-pandemic baseline values of mobility indicators for people in different age groups are shown in Fig. 11(a–e). Regarding the number of visited places, people aged 40 to 59 years showed the highest value, followed by people aged 25 to 39 years and people under 24 years. Regarding the other four indicators, people aged 25 to 39 years showed the highest value, followed by people aged 40 to 59 years and people under 24 years. People aged over 60 years showed the lowest value for all indicators. Fig. 11(f) shows the significance (p-value of ANOVA test) of the differences between any two groups of population, where 1 represents people under 24 years, 2 represents people aged 25 to 39 years, 3 represents people aged 40 to 59 years, and 4 represents people aged over

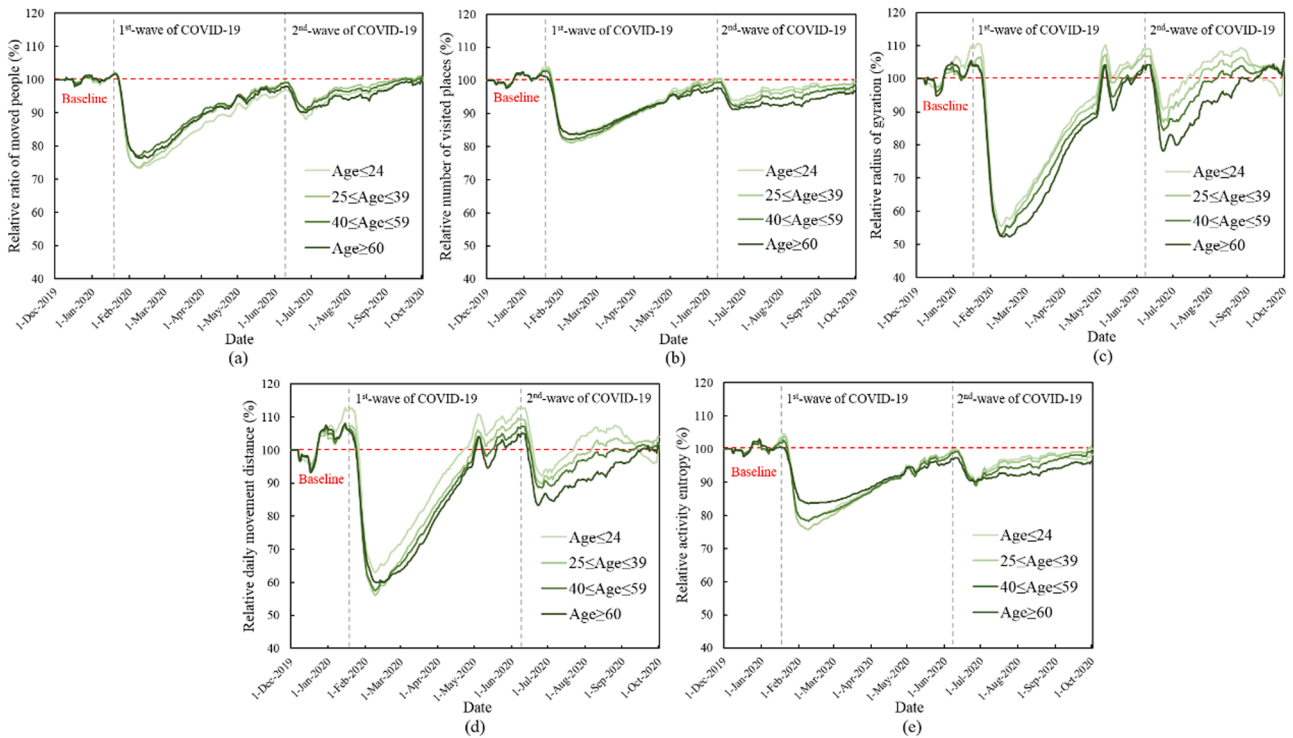


Fig. 12. Resilience curves of human mobility to COVID-19 for people in different age groups. (a) Ratio of moved people; (b) Number of visited places; (c) Radius of gyration; (d) Daily movement distance; (e) Activity entropy.

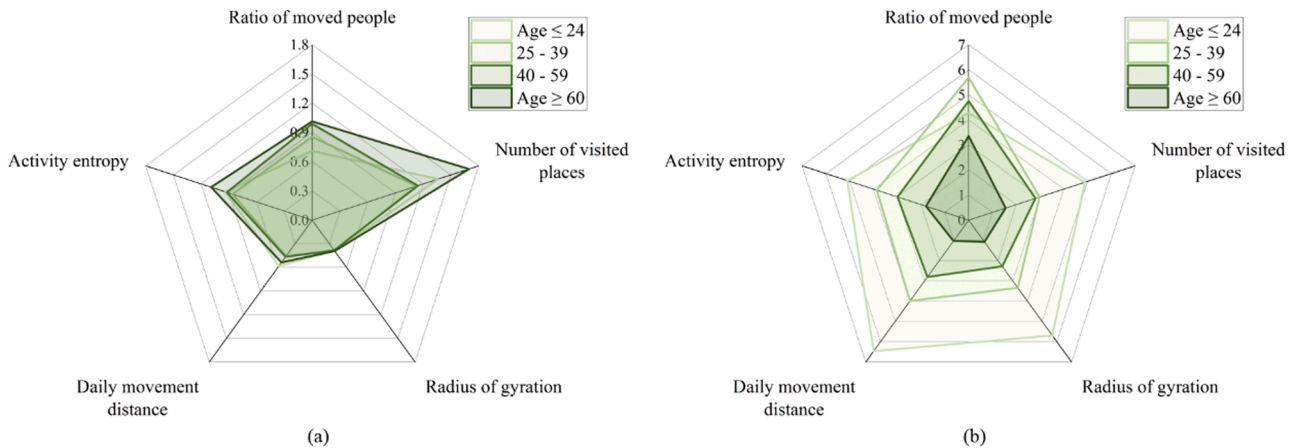


Fig. 13. Integrated resilience index of human mobility for people in different age groups. (a) The first wave of COVID-19; (b) The second wave of COVID-19.

60 years. The differences in all indicators between any two groups of population are significant except the ratio of moved people between people under 24 years and aged 40 to 59 years, number of visited places between people under 24 years and over 60 years and between people aged 25 to 39 years and aged 40 to 59 years, and activity entropy between people under 24 years and aged 40 to 59 years.

Compared to the baseline values, the resilience curves of human mobility to COVID-19 for people in different age groups are shown in Fig. 12. The change patterns of human mobility show significant differences among people in different age groups, indicating a high age heterogeneity in mobility resilience. Meanwhile, this heterogeneity exhibits different patterns among different mobility characteristics and in face of different waves of COVID-19 outbreaks. For example, regarding the ratio of moved people, people under 24 years show relatively high speed of disruption, large value of maximum impact, and small speed of recovery, whereas regarding the radius of gyration and daily movement

distance, people under 24 years show relatively small speed of disruption, small value of maximum impact, and high speed of recovery. Additionally, compared with the first wave of COVID-19, the degree of this heterogeneity is reinforced when facing the second wave of COVID-19. The detailed comparisons can be seen in the calculation results of the detailed mobility resilience metrics for people in different age groups as shown in Appendix Table A2.

Based on the detailed resilience metrics, the integrated resilience index of human mobility for people in different age groups are shown in Fig. 13. In face of the first wave of COVID-19, the age differences in mobility resilience are mainly reflected in the number of visited places and the ratio of moved people. Regarding the former, people aged over 60 years showed the highest resilience, followed by people under 24 years. The resilience of people aged 25 to 59 years was the lowest. Regarding the latter, people aged over 40 years showed the highest resilience, followed by people aged 25 to 39 years. The resilience of

people under 24 years was the lowest. Comparing the average resilience index of five indicators, people aged over 60 years showed the highest value (0.95), followed by people under 24 years (0.80) and people aged 40 to 59 years (0.78). The value of people aged 25 to 39 years (0.74) was the lowest.

In face of the second wave of COVID-19, the mobility resilience of people in all age groups increased, while their order of strength exhibited a completely different pattern. Regarding the ratio of moved people, people aged 25 to 39 years showed the highest resilience, followed by people aged 40 to 59 years and people under 24 years. Regarding the other four indicators, people under 24 years showed the highest resilience, followed by people aged 25 to 39 years and people aged 40 to 59 years. The resilience of people aged over 60 years was the lowest for all indicators. Comparing the average resilience index of five indicators, people aged under 24 years showed the highest value (5.28), followed by people aged 25 to 39 years (3.97) and people aged 40 to 59 years (3.13). The value of people aged over 60 years (1.76) was the lowest.

6. Discussion

In the above section, we observed that human mobility resilience to the COVID-19 pandemic exhibits significant heterogeneities and variations in different mobility characteristics, among people with different demographic attributes, and under different waves of outbreaks. In this section, we will further reveal the mechanism behind these heterogeneities and variations by discussing the potential influencing factors that may affect human mobility resilience and provide some implications for future sustainable and resilient urban management.

6.1. Potential influencing factors of human mobility resilience

In general, the potential influencing factors that may affect human mobility resilience to the pandemic can be divided into four aspects: pandemic spread characteristics, pandemic prevention measures, people's willingness to travel, and people's travel demand. In the following, we will discuss them by comparing the situations under two waves of COVID-19 outbreaks in Beijing and among people with different demographic attributes.

During the first wave of COVID-19 outbreak, the spread of disease was driven by the overlap of imported cases from other cities and the local infections. Therefore, the spatial range of the spread was relatively wide: the confirmed cases occurred in 15 districts and scattered throughout the main urban area (Guo et al., 2022). To prevent and control the spread, city-wide lockdown measures such as stopping of public transportation, closure of schools and businesses, ban on public gatherings, and promotion of remote working, were implemented (Beijing Municipal Health Commission, 2020). Such measures made the whole city enter a "closed-off" state and mobility of each person was greatly restricted. Meanwhile, because there were many unknowns and uncertainties about the pandemic during this stage, people's willingness to travel decreased to a minimum due to the psychological fear of the pandemic. Under the combined influence of the above factors, human mobility resilience exhibited low values in terms of all aspects of mobility characteristics, including mobility intensity, mobility range, and mobility diversity.

During the second wave of COVID-19 outbreak, the spread of disease was mainly caused by a clustering transmission in a wholesale market, Xinfadi market. Therefore, the spatial range of the spread was locally clustering: the confirmed cases occurred only in 11 districts and mainly distributed around the source of the outbreak (Guo et al., 2022). Meanwhile, as the transmission mechanism of the pandemic became clearer during this stage, more precise and differentiated pandemic prevention measures such as close contact tracing based on big data, rapid nucleic acid testing, and targeted closed-off management, were implemented (Tian et al., 2020b; Agbehadji et al., 2020; Huang et al.,

2022). Different from the city-wide lockdown measures during the first wave of outbreak, such improved measures only restricted mobility of people in infected communities, while people in other regions could move normally. In addition, people's willingness to travel increased due to their adaption to the pandemic and people's travel demands also increased due to the gradual resumption of work. As a result, human mobility resilience was significantly enhanced and especially, the resilience of the ratio of moved people became the highest.

Regarding people with different genders, the heterogeneities in their mobility resilience were mainly caused by the differences in their travel willingness and travel demands. Specifically, the mobility resilience of males was always higher than that of females. There are mainly two possible reasons for this. First, the decrease in the work-related travel demands during the pandemic was stronger for females than that for males because females were more likely to work in sectors harder-hit by the pandemic, such as services, retail, tourism, and hospitality (Flor et al., 2022). Second, the travel willingness of females was lower than that of males during the pandemic because females were more likely than males to stay at home and take responsibilities of household and childcare (Flor et al., 2022). Meanwhile, these gaps were exacerbated from the first to the second wave of outbreaks, because the work-related movement of males gradually recovered to the normal with the resumption of work, while that of females did not due to their higher unemployment rate.

Regarding people in different age groups, their mobility resilience showed different heterogeneity patterns during two waves of COVID-19 due to different influencing factors. During the first wave of COVID-19, their mobility resilience was mainly influenced by the city-wide lockdown measures. Such measures restricted the mobility of all citizens to an almost equal level. Therefore, older people who exhibited lower mobility indicator values before the pandemic contrarily showed relatively stronger resilience. During the second wave of COVID-19, the city-wide lockdown measures were lifted and people's mobility resilience was mainly influenced by their travel willingness and travel demands. Therefore, younger adults showed relatively higher resilience because they had to move normally to maintain their daily work and study, while older adults showed relatively lower resilience because their willingness to travel was still low due to the higher risk of infection or developing severe forms if infected (Applegate & Ouslander, 2020).

6.2. Implications for sustainable and resilient urban management

Different from existing studies that have only focused on the changes in human mobility during initial stage of COVID-19, our study presents the complete change process of human mobility over different stages of COVID-19 towards a multi-dimensional perspective. More importantly, the resilience of human mobility to COVID-19 is quantified and its heterogeneities and variations are revealed. These findings may provide valuable implications for sustainable and resilient urban management in response to later waves of COVID-19 or similar crises in the future.

First, some implications can be derived for the further refinement of pandemic-control measures. As the COVID-19 pandemic has continued for a long time, one essential issue needs to be focused on is how to balance pandemic prevention and control with normal social and economic development. The improvement of human mobility resilience from the first to the second wave of COVID-19 in our case study provides confidence and referential experience for this. Specifically, precise and differentiated pandemic prevention measures are suggested, while large scale and high intensity lockdown measures should be avoided. To achieve this, two aspects of works need to be strengthened. First, the source of outbreak should be quickly identified and completely locked down to minimize the spatial range of the spread as much as possible; Second, people with high risk of infection should be quickly identified and timely quarantined by applying digital tracing and rapid nucleic acid testing.

Second, some implications can be derived for the tackling of

Table A1
Detailed resilience metrics of human mobility to COVID-19 for people with different genders.

		The first wave of COVID-19					The second wave of COVID-19				
		R	N	Rog	D	AE	R	N	Rog	D	AE
Speed of disruption	Male	1.35	1.10	2.93	2.71	1.29	0.49	0.53	1.85	1.15	0.66
	Female	1.51	1.07	3.24	2.83	1.27	0.63	0.62	2.00	1.82	0.67
Maximum impact (%)	Male	23.33	18.25	46.95	43.17	22.50	7.83	7.45	14.78	10.36	9.91
	Female	26.31	17.59	49.24	43.08	22.36	9.46	7.51	17.98	14.55	10.07
Speed of recovery	Male	0.18	0.16	0.57	0.54	0.19	0.11	0.07	0.44	0.23	0.10
	Female	0.19	0.14	0.60	0.53	0.16	0.15	0.07	0.57	0.29	0.12
Recovery degree	Male	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00	1.00	1.00
	Female	1.00	0.99	1.00	1.00	0.99	1.00	1.00	1.00	1.00	1.00
Duration of impact (d)	Male	147	136	101	98	140	89	111	41	53	111
	Female	157	136	100	100	155	81	112	42	56	99
Total performance loss	Male	14.78	12.67	25.67	23.10	15.54	3.03	4.15	2.77	2.44	4.27
	Female	18.18	13.55	28.12	24.24	18.10	4.38	5.34	3.95	3.58	6.09

Note: R, N, Rog, D, and AE denote ratio of moved people, number of visited places, radius of gyration, daily movement distance, and activity entropy.

intensified social inequality problem during the pandemic. The social inequality, a common problem existed in many cities, is exacerbated during COVID-19 owing to the disproportionate impact of the pandemic on vulnerable individuals (Van Dorn et al., 2020; Blundell et al., 2020; Feng et al., 2022). Actually, the reasons behind such disproportionate impact are differences in people’s response capabilities to the pandemic, which we measured as mobility resilience. Therefore, based on the resilience disparities detected in our case study, some targeted support policies are suggested. Specifically, females usually experience higher rates of unemployment during pandemics, therefore, more job opportunities should be provided for them. For example, some new forms of employment can be supported such as e-commerce, online education, and online entertainment. Additionally, older adults usually exhibit lower resilience than other groups, therefore, targeted social assistance such as home medical service, procurement and delivery service should be provided for them to meet their basic needs.

Third, some implications can be derived for the promotion of sustainable city recovery during the post-pandemic era. The intensity of human mobility has been widely used in existing studies as a measurement to evaluate the city recovery after a disaster (Podesta et al., 2021; Hong et al., 2021; Liu et al., 2021b). However, the heterogeneity in change patterns and resilience capabilities of different mobility characteristics in our findings suggests that in addition to focusing on mobility intensity, the mobility range and diversity should also be considered. Specifically, city recovery is a multi-dimensional process, therefore, in addition to ensuring people’s compulsory mobility such as commuting, appropriate stimulus policy should be implemented to stimulate people’s mobility related to shopping, traveling and other types of social and economic activities, which better reflect the vitality of a city.

7. Conclusions and future work

Based on the change process of human mobility over different stages of COVID-19 extracted from longitudinal mobile phone signaling data, we introduced an integrated framework to quantify human mobility resilience. Taking Beijing as a case study, we compared the resilience of different mobility characteristics among people with different attributes, and in face of different waves of COVID-19 outbreaks. The main conclusions are summarized as follows:

- (1) Different mobility characteristics exhibited different resilience to COVID-19. The mobility range and diversity were less resilient than people’s willingness to engage in a movement. Compared to the ratio of moved people, which denotes the willingness to move, the radius of gyration and daily movement distance of moved people was most affected by COVID-19 even though it exhibited a high speed of recovery; the activity entropy of moved

people was less affected by COVID-19 but exhibited a slow speed of recovery.

- (2) The mobility resilience of people with different attributes showed significant disparities. Females consistently showed lower resilience than males, which exacerbated the existing mobility gaps between them. Middle-aged and young people showed lower resilience under the first wave of COVID-19 due to the large scale and high intensity mobility restrictions. As such measures were lifted, the resilience of older adult became the lowest because they were more likely to reduce mobility given the higher risk of infection.
- (3) With the refinement of pandemic-control measures over time, human mobility resilience has been enhanced. During the first wave of COVID-19, city-wide lockdown measures were implemented to mitigate the spread of the pandemic, which restricted mobility of all citizens and weakened their resilience. Whereas, during the second wave of COVID-19, such measures became precise and locally targeted, which ensured the normal mobility of citizens as much as possible while effectively preventing and controlling the pandemic.

The main significance of this study lies in two aspects. Academically, an integrated human mobility resilience assessment framework in the context of pandemic outbreaks has been introduced. This framework can be applied not only in Beijing but also in other cities to estimate the resilience of human mobility to COVID-19 or other types of pandemics. Moreover, this integrated framework can also be replicated for investigating human mobility resilience to other type of exceptional or extreme events (e.g. natural disasters and man-made risks) more accurately and comprehensively. In practice, the findings provide valuable references for the coordination of pandemic prevention and control with normal social and economic development. Precise and differentiated mobility restriction measures are recommended to effectively control the spread of the pandemic while ensuring the normal mobility of citizens as much as possible; targeted support policies are suggested to support more reasonable resource allocations and minimize resilience heterogeneity among different population groups, which can help avoid problems of social inequity.

This study also has several limitations. First, due to the limitation of data acquisition, data for only one month before the COVID-19 was used to calculate the baseline value of human mobility, which might not be very accurate. In the future, longer-term data should be collected to measure the normal trends of human mobility more accurately. Second, only changes in human mobility over the first two waves of COVID-19 outbreak in 2020 were analyzed and the data was not timely updated. However, since the COVID-19 has lasted for over two years, many things as well as human mobility behavior in response to COVID-19 may change. In the future, the recent data should be collected and analyzed

Table A2
Detailed resilience metrics of human mobility to COVID-19 for people in different age groups.

		The first wave of COVID-19					The second wave of COVID-19				
		R	N	Rog	D	AE	R	N	Rog	D	AE
Speed of disruption	Age<24	1.54	1.01	3.32	2.76	1.30	0.55	0.49	1.75	1.15	0.61
	25≤Age<39	1.55	1.18	3.25	2.92	1.46	0.62	0.69	1.85	1.14	0.71
	40≤Age≤59	1.35	1.08	2.96	2.69	1.23	0.54	0.50	1.82	1.17	0.66
	Age≥60	1.23	0.64	2.72	2.24	0.83	0.52	0.54	2.33	1.90	0.48
Maximum impact (%)	Age<24	26.67	16.03	44.49	37.05	21.51	8.81	6.79	10.51	9.22	9.75
	25≤Age<39	26.49	18.79	47.48	43.94	24.27	9.23	7.57	14.79	10.23	10.62
	40≤Age≤59	22.92	17.93	47.10	42.49	21.71	8.11	7.53	16.35	11.66	9.94
	Age≥60	23.63	16.33	47.65	40.06	16.44	7.83	6.42	23.27	17.11	7.20
Speed of recovery	Age<24	0.17	0.15	0.56	0.51	0.17	0.15	0.08	0.47	0.32	0.15
	25≤Age<39	0.20	0.16	0.61	0.55	0.20	0.14	0.08	0.45	0.25	0.12
	40≤Age≤59	0.18	0.14	0.58	0.52	0.17	0.11	0.07	0.36	0.20	0.11
	Age≥60	0.17	0.12	0.60	0.50	0.11	0.11	0.06	0.35	0.20	0.06
Recovery degree	Age<24	1.00	1.00	1.00	1.00	1.00	1.00	0.99	1.00	1.00	0.99
	25≤Age<39	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	40≤Age≤59	1.00	0.99	1.00	1.00	0.99	1.00	0.99	1.00	1.00	1.00
	Age≥60	1.00	0.98	1.00	1.00	0.97	1.00	0.99	1.00	1.00	0.99
Duration of impact (d)	Age<24	177	122	97	88	140	76	80	27	36	77
	25≤Age<39	151	136	99	98	143	81	111	39	51	109
	40≤Age≤59	149	140	101	99	141	87	112	55	71	112
	Age≥60	163	141	102	100	142	90	112	75	96	112
Total performance loss	Age<24	20.34	11.43	23.18	17.50	15.54	4.53	2.48	1.15	1.42	3.24
	25≤Age<39	16.90	13.34	25.00	22.61	16.91	3.03	3.76	2.41	2.54	4.25
	40≤Age≤59	15.11	13.25	27.24	23.77	16.41	3.57	5.10	3.95	3.74	5.51
	Age≥60	16.60	13.01	30.01	24.68	14.45	5.23	7.09	7.94	8.08	7.71

Note: R, N, Rog, D, and AE denote ratio of moved people, number of visited places, radius of gyration, daily movement distance, and activity entropy.

so as to make a comparison with the results obtained from this study. Third, the potential influencing factors that may affect human mobility resilience to the pandemic were only qualitatively discussed in the discussion section, which is insufficient. In the future, a quantitative relationship model between them should be constructed to better reveal the mechanism behind the heterogeneities and variations of human mobility resilience.

Funding

This work was supported by the National Key Research & Development Program of China (Grant No. 2022YFC3800803) and the National Natural Science Foundation of China (NSFC) (Grant Nos. 42071436 and 42101431).

Declaration of Competing Interest

No potential conflict of interest was reported by the authors.

Data availability

The data that has been used is confidential.

Appendix

References

Agbehadji, I. E., Awuzie, B. O., Ngowi, A. B., & Millham, R. C. (2020). Review of big data analytics, artificial intelligence and nature-inspired computing models towards accurate detection of COVID-19 pandemic cases and contact tracing. *International Journal of Environmental Research and Public Health*, 17(15), 5330.

Alessandretti, L. (2022). What human mobility data tell us about COVID-19 spread. *Nature Reviews Physics*, 4(1), 12–13.

Applegate, W. B., & Ouslander, J. G. (2020). COVID-19 presents high risk to older persons. *Journal of the American Geriatrics Society*, 68(4), 681.

Assumma, V., Bottero, M., De Angelis, E., Lourenço, J. M., Monaco, R., & Soares, A. J. (2021). A decision support system for territorial resilience assessment and planning:

An application to the Douro Valley (Portugal). *Science of The Total Environment*, 756, Article 143806.

Beijing Municipal Health Commission. (2020, February 1). Notice on the issuance of the work plan for the COVID-19 epidemic prevention and control in the near future. Retrieved from http://wjw.beijing.gov.cn/wjwh/ztlz/xgzbd/gzbdzcfg/202002/t20200201_1622567.html.

Beijing Municipal Health Commission. (2022, August 12). Information on the prevention and control of the COVID-19 epidemic in Beijing. Retrieved from <http://wjw.beijing.gov.cn/wjwh/ztlz/xgzbd/>.

Batty, M. (2022). The COVID years: Predictable unpredictability. *Environment and Planning B: Urban Analytics and City Science*, 49(1), 3–6.

Benita, F. (2021). Human mobility behavior in COVID-19: A systematic literature review and bibliometric analysis. *Sustainable Cities and Society*, 70, Article 102916.

Beria, P., & Lunkar, V. (2021). Presence and mobility of the population during the first wave of Covid-19 outbreak and lockdown in Italy. *Sustainable Cities and Society*, 65, Article 102616.

Bhamra, R., Dani, S., & Burnard, K. (2011). Resilience: The concept, a literature review and future directions. *International Journal of Production Research*, 49(18), 5375–5393.

Blundell, R., Costa Dias, M., Joyce, R., & Xu, X. (2020). COVID-19 and Inequalities. *Fiscal Studies*, 41(2), 291–319.

Bonaccorsi, G., Pierri, F., Cinelli, M., Flori, A., Galeazzi, A., Porcelli, F., Schmidt, A. L., Valensise, C. M., Scala, A., Quattrociochi, W., & Pammolli, F. (2020). Economic and social consequences of human mobility restrictions under COVID-19. *Proceedings of the National Academy of Sciences*, 117(27), 15530–15535.

Bruneau, M., Chang, S. E., Eguchi, R. T., Lee, G. C., O'Rourke, T. D., Reinhorn, A. M., Shinozuka, M., Tierney, K., Wallace, W. A., & Von Winterfeldt, D. (2003). A framework to quantitatively assess and enhance the seismic resilience of communities. *Earthquake Spectra*, 19(4), 733–752.

Carella, G., Pérez Trufero, J., Álvarez, M., & Mateu, J. (2022). A Bayesian spatial analysis of the heterogeneity in human mobility changes during the first wave of the COVID-19 Epidemic in the United States. *The American Statistician*, 76(1), 64–72.

Calabrese, F., Diao, M., Di Lorenzo, G., Ferreira Jr., J., & Ratti, C. (2013). Understanding individual mobility patterns from urban sensing data: A mobile phone trace example. *Transportation Research Part C: Emerging Technologies*, 26, 301–313.

Chen, X., Xia, E., & He, T. (2020). Influence of traveler risk perception on the willingness to travel in a major epidemic. *International Journal of Sustainable Development and Planning*, 15(6), 901–909.

Coccia, M. (2022). Preparedness of countries to face COVID-19 pandemic crisis: Strategic positioning and factors supporting effective strategies of prevention of pandemic threats. *Environmental Research*, 203, Article 111678.

Csáji, B. C., Browet, A., Traag, V. A., Delvenne, J. C., Huens, E., Van Dooren, P., Smoreda, Z., & Blondel, V. D. (2013). Exploring the mobility of mobile phone users. *Physica A: Statistical Mechanics and its Applications*, 392(6), 1459–1473.

Czech, K., Davy, A., & Wielechowski, M. (2021). Does the COVID-19 pandemic change human mobility equally worldwide? Cross-country cluster analysis. *Economics*, 9(4), 182.

da Mata Martins, M. C., da Silva, A. N. R., & Pinto, N. (2019). An indicator-based methodology for assessing resilience in urban mobility. *Transportation Research Part D: Transport and Environment*, 77, 352–363.

- Eyawo, O., Viens, A. M., & Ugoji, U. C. (2021). Lockdowns and low-and middle-income countries: Building a feasible, effective, and ethical COVID-19 response strategy. *Globalization and Health*, 17(1), 1–5.
- Feng, S., Zhai, Y., Wei, W., Tan, Y., Geng, Y., & Nie, W. (2022). Sustainable social development promotes COVID-19 pandemic control. *Science*, 25(7), Article 104592.
- Flor, L. S., Friedman, J., Spencer, C. N., Cagney, J., Arrieta, A., Herbert, M. E., ... Gakidou, E. (2022). Quantifying the effects of the COVID-19 pandemic on gender equality on health, social, and economic indicators: A comprehensive review of data from March, 2020, to September, 2021. *The Lancet*, 399, 2381–2397.
- Galeazzi, A., Cinelli, M., Bonaccorsi, G., Pierri, F., Schmidt, A. L., Scala, A., Pammolli, F., & Quattrocchi, W. (2021). Human mobility in response to COVID-19 in France, Italy and UK. *Scientific Reports*, 11(1), 1–10.
- Gauvin, L., Tizzoni, M., Piaggese, S., Young, A., Adler, N., Verhulst, S., Ferres, L., & Cattuto, C. (2020). Gender gaps in urban mobility. *Humanities and Social Sciences Communications*, 7(1), 1–13.
- LSHTM CMMID COVID-19 working group Gibbs, H., Liu, Y., Pearson, C. A., Jarvis, C. I., Grundy, C., Quilty, B. J., Diamond, C., & Eggo, R. M. (2020). Changing travel patterns in China during the early stages of the COVID-19 pandemic. *Nature Communications*, 11(1), 1–9.
- Gonzalez, M. C., Hidalgo, C. A., & Barabasi, A. L. (2008). Understanding individual human mobility patterns. *Nature*, 453(7196), 779–782.
- Gobatoni, F., Pelorosso, R., Lauro, G., Leone, A., & Monaco, R. (2011). A procedure for mathematical analysis of landscape evolution and equilibrium scenarios assessment. *Landscape and Urban Planning*, 103(3–4), 289–302.
- Guo, W., Feng, Y., Luo, W., Ren, Y., Tan, J., Jiang, X., & Xue, Q. (2022). The impacts of COVID-19 and policies on spatial and temporal distribution characteristics of traffic: Two examples in Beijing. *Sustainability*, 14(3), 1733.
- Hong, B., Bonczak, B. J., Gupta, A., & Kontokosta, C. E. (2021). Measuring inequality in community resilience to natural disasters using large-scale mobility data. *Nature Communications*, 12(1), 1–9.
- Hosseini, S., Barker, K., & Ramirez-Marquez, J. E. (2016). A review of definitions and measures of system resilience. *Reliability Engineering & System Safety*, 145, 47–61.
- Hoteit, S., Secci, S., Sobolevsky, S., Ratti, C., & Pujolle, G. (2014). Estimating human trajectories and hotspots through mobile phone data. *Computer Networks*, 64, 296–307.
- Holling, C. S. (1973). Resilience and stability of ecological systems. *Annual Review of Ecology and Systematics*, 1–23.
- Huang, Q., Liu, Q., Song, C., Liu, X., Shu, H., Wang, X., Liu, Y., Chen, X., Chen, J., & Pei, T. (2022). Urban spatial epidemic simulation model: A case study of the second COVID-19 outbreak in Beijing, China. *Transactions in GIS*, 26(1), 297–316.
- Iftakhar, E. N., Priesemann, V., Balling, R., Bauer, S., Beutels, P., Valdez, A. C., ... Willeit, P. (2021). A look into the future of the COVID-19 pandemic in Europe: An expert consultation. *The Lancet Regional Health-Europe*, 8, Article 100185.
- Jay, J., Bor, J., Nsoesie, E. O., Lipsen, S. K., Jones, D. K., Galea, S., & Raifman, J. (2020). Neighbourhood income and physical distancing during the COVID-19 pandemic in the United States. *Nature Human Behaviour*, 4(12), 1294–1302.
- Kishore, N., Kiang, M. V., Engo-Monsen, K., Vembar, N., Schroeder, A., Balsari, S., & Buckee, C. O. (2020). Measuring mobility to monitor travel and physical distancing interventions: A common framework for mobile phone data analysis. *The Lancet Digital Health*, 2(11), e622–e628.
- Kontokosta, C. E., & Malik, A. (2018). The Resilience to Emergencies and Disasters Index: Applying big data to benchmark and validate neighborhood resilience capacity. *Sustainable Cities and Society*, 36, 272–285.
- Lee, M., Zhao, J., Sun, Q., Pan, Y., Zhou, W., Xiong, C., & Zhang, L. (2020). Human mobility trends during the early stage of the COVID-19 pandemic in the United States. *PLoS One*, 15(11), Article e0241468.
- Lenormand, M., Louail, T., Cantú-Ros, O. G., Picornell, M., Herranz, R., Arias, J. M., Barthelemy, M., Miguel, M. S., & Ramasco, J. J. (2015). Influence of sociodemographic characteristics on human mobility. *Scientific Reports*, 5(1), 1–15.
- Li, M., Gao, S., Lu, F., & Zhang, H. (2019). Reconstruction of human movement trajectories from large-scale low-frequency mobile phone data. *Computers, Environment and Urban Systems*, 77, Article 101346.
- Liu, Y., Wang, Z., Rader, B., Li, B., Wu, C. H., Whittington, J. D., Zheng, P., Stenseth, N. C., Bjornstad, N. O., Brownstein, J. S., & Tian, H. (2021a). Associations between changes in population mobility in response to the COVID-19 pandemic and socioeconomic factors at the city level in China and country level worldwide: A retrospective, observational study. *The Lancet Digital Health*, 3(6), e349–e359.
- Liu, Y., Ma, S., & Mu, R. (2021b). Uneven recovery from the COVID-19 pandemic: Post-lockdown human mobility across Chinese cities. IZA Discussion Paper No. 14187, Available at SSRN: <https://ssrn.com/abstract=3808450>.
- Lu, Y. H., Zhang, H., Zhuang, M., Hu, M., Zhang, C., Pan, J., Liu, P., & Zhang, J. (2022). Understanding regional mobility resilience and its relationship with regional culture during the COVID-19 pandemic: A pathogen-stress theory perspective. *Journal of Cleaner Production*, 339, Article 130621.
- Luo, F., Cao, G., Mulligan, K., & Li, X. (2016). Explore spatiotemporal and demographic characteristics of human mobility via Twitter: A case study of Chicago. *Applied Geography*, 70, 11–25.
- Meerow, S., Newell, J. P., & Stults, M. (2016). Defining urban resilience: A review. *Landscape and Urban Planning*, 147, 38–49.
- Mu, X., Fang, C., Yang, Z., & Guo, X. (2022). Impact of the COVID-19 epidemic on population mobility networks in the Beijing–Tianjin–Hebei Urban agglomeration from a resilience perspective. *Land*, 11(5), 675.
- Mu, X., Yeh, A. G. O., & Zhang, X. (2021). The interplay of spatial spread of COVID-19 and human mobility in the urban system of China during the Chinese New Year. *Environment and Planning B: Urban Analytics and City Science*, 48(7), 1955–1971.
- Mueller, J. T., McConnell, K., Burrow, P. B., Pofahl, K., Merdjanoff, A. A., & Farrell, J. (2021). Impacts of the COVID-19 pandemic on rural America. In , 118. *Proceedings of the National Academy of Sciences*, Article 2019378118.
- Nan, C., & Sansavini, G. (2017). A quantitative method for assessing resilience of interdependent infrastructures. *Reliability Engineering & System Safety*, 157, 35–53.
- Olivieri, C., & Fageda, X. (2021). Urban mobility with a focus on gender: The case of a middle-income Latin American city. *Journal of Transport Geography*, 91, Article 102996.
- Pan, Y., Darzi, A., Kabiri, A., Zhao, G., Luo, W., Xiong, C., & Zhang, L. (2020). Quantifying human mobility behaviour changes during the COVID-19 outbreak in the United States. *Scientific Reports*, 10(1), 1–9.
- Pappalardo, L., Vanhoof, M., Gabrielli, L., Smoreda, Z., Pedreschi, D., & Giannotti, F. (2016). An analytical framework to nowcast well-being using mobile phone data. *International Journal of Data Science and Analytics*, 2(1), 75–92.
- Peak, C. M., Wesolowski, A., zu Erbach-Schoenberg, E., Tatem, A. J., Wetter, E., Lu, X., ... Bengtsson, L. (2018). Population mobility reductions associated with travel restrictions during the Ebola epidemic in Sierra Leone: Use of mobile phone data. *International Journal of Epidemiology*, 47(5), 1562–1570.
- Podesta, C., Coleman, N., Esmalian, A., Yuan, F., & Mostafavi, A. (2021). Quantifying community resilience based on fluctuations in visits to points-of-interest derived from digital trace data. *Journal of the Royal Society Interface*, 18(177), Article 20210158.
- Pullano, G., Valdano, E., Scarpa, N., Rubrichi, S., & Colizza, V. (2020). Evaluating the effect of demographic factors, socioeconomic factors, and risk aversion on mobility during the COVID-19 epidemic in France under lockdown: A population-based study. *The Lancet Digital Health*, 2(12), e638–e649.
- Rao, S., Gamage, S., Arnold, J., & Anderson, E. (2021). Human mobility, COVID-19, and policy responses: The rights and claims-making of migrant domestic workers. *Feminist Economics*, 27(1–2), 254–270.
- Roy, K. C., Cebrían, M., & Hasan, S. (2019). Quantifying human mobility resilience to extreme events using geo-located social media data. *EPJ Data Science*, 8(1), 18.
- Schwarz, S. (2018). Resilience in psychology: A critical analysis of the concept. *Theory & Psychology*, 28(4), 528–541.
- Sharifi, A., & Khavarian-Garmsir, A. R. (2020). The COVID-19 pandemic: Impacts on cities and major lessons for urban planning, design, and management. *Science of the Total Environment*, 749, Article 142391.
- Song, C., Qu, Z., Blumm, N., & Barabási, A. L. (2010). Limits of predictability in human mobility. *Science*, 327(5968), 1018–1021.
- Song, Y., Liu, Y., Qiu, W., Qin, Z., Tan, C., Yang, C., & Zhang, D. (2020). MIF: Human mobility extractions with cellular signaling data under spatio-temporal uncertainty. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, 4(4), 1–19.
- Škare, M., Soriano, D. R., & Porada-Rochoń, M. (2021). Impact of COVID-19 on the travel and tourism industry. *Technological Forecasting and Social Change*, 163, Article 120469.
- Tan, S., Lai, S., Fang, F., Cao, Z., Sai, B., Song, B., ... Lu, X. (2021). Mobility in China, 2020: A tale of four phases. *National Science Review*, 8(11), nwab148.
- Tian, H., Liu, Y., Li, Y., Wu, C. H., Chen, B., Kraemer, M. U., ... Dye, C. (2020a). An investigation of transmission control measures during the first 50 days of the COVID-19 epidemic in China. *Science*, 368(6491), 638–642.
- Tian, S., Hu, N., Lou, J., Chen, K., Kang, X., Xiang, Z., ... Zhang, J. (2020b). Characteristics of COVID-19 infection in Beijing. *Journal of Infection*, 80(4), 401–406.
- Tu, W., Cao, J., Yue, Y., Shaw, S. L., Zhou, M., Wang, Z., Chang, X., Xu, Y., & Li, Q. (2017). Coupling mobile phone and social media data: A new approach to understanding urban functions and diurnal patterns. *International Journal of Geographical Information Science*, 31(12), 2331–2358.
- Turner, M. G., & Gardner, R. H. (2015). Landscape metrics. *Landscape Ecology in Theory and Practice* (pp. 97–142). New York, NY: Springer.
- Van Dorn, A., Cooney, R. E., & Sabin, M. L. (2020). COVID-19 exacerbating inequalities in the US. *The Lancet*, 395(10232), 1243–1244.
- Wang, Q., & Taylor, J. E. (2014). Quantifying human mobility perturbation and resilience in Hurricane Sandy. *PLoS One*, 9(11), Article e112608.
- Wang, Q., & Taylor, J. E. (2015). Resilience of human mobility under the influence of typhoons. *Procedia Engineering*, 118, 942–949.
- Wang, Q., & Taylor, J. E. (2016). Patterns and limitations of urban human mobility resilience under the influence of multiple types of natural disaster. *PLoS One*, 11(1), Article e0147299.
- Weill, J. A., Stigler, M., Deschenes, O., & Springborn, M. R. (2020). Social distancing responses to COVID-19 emergency declarations strongly differentiated by income. In , 117. *Proceedings of the National Academy of Sciences* (pp. 19658–19660).
- Wang, J., Huang, J., Yang, H., & Levinson, D. (2022). Resilience and recovery of public transport use during COVID-19. *npj Urban Sustainability*, 2(1), 1–9.
- Wang, S., Liu, Y., & Hu, T. (2020). Examining the change of human mobility adherent to social restriction policies and its effect on COVID-19 cases in Australia. *International Journal of Environmental Research and Public Health*, 17(21), 7930.
- Wang, W., Pei, T., Chen, J., Song, C., Wang, X., Shu, H., Ma, T., & Du, Y. (2019). Population distributions of age groups and their influencing factors based on mobile phone location data: A case study of Beijing, China. *Sustainability*, 11(24), 7033.
- Xi, W., Pei, T., Liu, Q., Song, C., Liu, Y., Chen, X., ... Zhang, Z. (2020). Quantifying the time-lag effects of human mobility on the COVID-19 transmission: A multi-city study in China. *IEEE Access*, 8, 216752–216761.
- Xia, F., Wang, J., Kong, X., Wang, Z., Li, J., & Liu, C. (2018). Exploring human mobility patterns in urban scenarios: A trajectory data perspective. *IEEE Communications Magazine*, 56(3), 142–149.

- Xu, Y., Belyi, A., Bojic, I., & Ratti, C. (2018). Human mobility and socioeconomic status: Analysis of Singapore and Boston. *Computers, Environment and Urban Systems*, *72*, 51–67.
- Xu, Y., Shaw, S. L., Zhao, Z., Yin, L., Lu, F., Chen, J., Fang, Z., & Li, Q. (2016). Another tale of two cities: Understanding human activity space using actively tracked cellphone location data. *Annals of the American Association of Geographers*, *106*(2), 489–502.
- Xu, Y., Xue, J., Park, S., & Yue, Y. (2021). Towards a multidimensional view of tourist mobility patterns in cities: A mobile phone data perspective. *Computers, Environment and Urban Systems*, *86*, Article 101593.
- Yang, C., Xiao, M., Ding, X., Tian, W., Zhai, Y., Chen, J., ... Ye, X. (2019a). Exploring human mobility patterns using geo-tagged social media data at the group level. *Journal of Spatial Science*, *64*(2), 221–238.
- Yabe, T., Tsubouchi, K., Fujiwara, N., Wada, T., Sekimoto, Y., & Ukkusuri, S. V. (2020). Non-compulsory measures sufficiently reduced human mobility in Tokyo during the COVID-19 epidemic. *Scientific Reports*, *10*(1), 1–9.
- Yang, F., Yao, Z., Ding, F., Tan, H., & Ran, B. (2019b). Understanding urban mobility pattern with cellular phone data: A case study of residents and travelers in Nanjing. *Sustainability*, *11*(19), 5502.
- Yin, L., Lin, N., & Zhao, Z. (2021). Mining daily activity chains from large-scale mobile phone location data. *Cities*, *109*, Article 103013.
- Zhang, M., Wang, S., Hu, T., Fu, X., Wang, X., Hu, Y., ... Bao, S. (2022). Human mobility and COVID-19 transmission: A systematic review and future directions. *Annals of GIS*, 1–14.
- Zhang, N., Jia, W., Wang, P., Dung, C. H., Zhao, P., Leung, K., Su, B., Cheng, R., & Li, Y. (2021). Changes in local travel behaviour before and during the COVID-19 pandemic in Hong Kong. *Cities*, *112*, Article 103139.
- Zhang, F., Li, Z., Li, N., & Fang, D. (2019). Assessment of urban human mobility perturbation under extreme weather events: A case study in Nanjing, China. *Sustainable Cities and Society*, *50*, Article 101671.
- Zhao, Z., Yin, L., Shaw, S. L., Fang, Z., Yang, X., & Zhang, F. (2018). Identifying stops from mobile phone location data by introducing uncertain segments. *Transactions in GIS*, *22*(4), 958–974.
- Zhou, Y., Xu, R., Hu, D., Yue, Y., Li, Q., & Xia, J. (2020). Effects of human mobility restrictions on the spread of COVID-19 in Shenzhen, China: A modelling study using mobile phone data. *The Lancet Digital Health*, *2*(8), e417–e424.
- Zhou, S., Zhou, S., Zheng, Z., & Lu, J. (2021). Optimizing spatial allocation of COVID-19 vaccine by agent-based spatiotemporal simulations. *GeoHealth*, *5*(6), e2021GH000427.