Annals of Tourism Research 98 (2023) 103522

Contents lists available at ScienceDirect

Annals of Tourism Research

journal homepage: https://www.journals.elsevier.com/annals-of-tourism-research

Changes in tourist mobility after COVID-19 outbreaks☆

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ARTICLE INFO

Article history:
Received 18 April 2022
Received in revised form 7 November 2022
Accepted 13 November 2022
Available online 2 December 2022

Handling Editor: Yang Yang

Keywords:
The COVID-19 pandemic
Tourist mobility
Human travel behavior
Big data
China

ABSTRACT

We comparatively examined tourist mobility changes in the entire country and explicitly covered two distinct waves of COVID-19 outbreaks, based on mobile phone data from 277.15 million tourists from 2019 to 2021 in China. The results show that domestic tourism in Beijing was even higher after the pandemic than prior to it. In addition, we found that female and elderly groups had a slower recovery after the first wave, whereas this was the opposite one year later, after the second wave. Additionally, wealthier, larger cities were notably hit the hardest. Overall, our findings provide a better understanding of tourism management in public health crises and policy-making during post-pandemic recovery and for future outbreaks.

Introduction

Tourism plays an indispensable role in the United Nations Sustainable Development Goals (World Tourism Organization, 2022a). As the fastest and largest growing sector during the last few decades, tourism has become a key driver for economic growth and social development (Lenzen et al., 2018; Rastegar et al., 2021). According to the World Travel & Tourism Council (WTTC) report (2021), tourism created 10.6 % of all jobs (334 million) worldwide, contributing to 10.4 % of the global GDP (US$9.2 trillion) prior to the pandemic in 2019. For many countries, domestic tourism contributes a significant portion to the tourism sector. For example, in China, tourism's contribution to the country's economic GDP was $1.72 trillion, accounting for 11.05 % of the total GDP in 2019 (Ministry of Culture and Tourism of the People's Republic of China, 2020).

All over the world, tourist mobility has been significantly affected by the ongoing COVID-19 pandemic (Gössling et al., 2020; He et al., 2022; Sharma et al., 2021; Uglis et al., 2022). According to United Nations World Tourism Organization (UNWTO) data (2021), global international arrivals dropped by 74 % in 2020 compared with 2019, leading to a potential $2.4 trillion loss in international tourism revenue (United Nations News, 2021). In many countries, assessing tourist mobility changes due to COVID-19 is important for reaching sustainable development goals and implementing policies for post-pandemic economic recovery (Guerriero et al., 2020; Matsuura & Saito, 2022). However, tourist mobility changes following the outbreak of COVID-19 remain unclear due to a lack of accurate data from before and after the outbreaks. In addition, due to the ongoing pandemic's multiple waves and variants appearing successively (Callaway, 2021), the majority of countries have experienced recurring outbreaks

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https://doi.org/10.1016/j.annals.2022.103522
0160-7383/

(Aleta et al., 2020). During the past two years, tourism has experienced continuous 'rises and falls' that have become the new norm. Thus, there is a current need to explore the changes in tourists' mobility after multiple outbreak waves using mobile phone data.

Data-driven research strongly hinges on the quality of data. The cell phone mobility data used in this study has benefits regarding long-term (i.e., three years), high temporal resolution (i.e., daily basis), and large-scale (i.e., all over China) human mobility behavior (Huang et al., 2022; Kar et al., 2021; Levin et al., 2021), which enables us to comprehensively understand the changes in tourist mobility before and after COVID-19 outbreaks. Here, we take Beijing as the destination and compare two waves during the same months in a row - during the first wave at the start of 2020, and during the second wave at the start of 2021 - by using three years mobile phone data from 277.15 million tourists. The data span the pre- and post-pandemic periods, covering 254 cities in China and capturing the daily inter-city tourist movements with socio-demographic information. China's capital city, Beijing, was selected as the case study to answer these questions, since it suffered from both waves during the same months in 2020 and 2021, creating an effective chance of comparing the first- and second-wave impacts on tourist mobility. As well, Beijing is the center of the country's economy and culture and is one of the main domestic tourist-friendly destinations. Furthermore, major cities are more likely to experience recurring outbreaks due to extensive human mobility.

Three main research questions will be addressed in this exploratory study:

- RQ1: How did overall domestic tourist mobility change in response to COVID-19 during different outbreak waves?
- RQ2: How did such changes vary among different socio-demographic tourists?
- RQ3: How did such changes differ from one city to another?

The main contributions of this study can be summarized as follows: Firstly, by using unparalleled mobile phone data, we monitor the dynamic changes in China's tourist mobility in response to COVID-19 during the whole outbreak, as well as during multiple waves. Secondly, we reveal the social demographic disparities and spatial heterogeneity in tourist mobility changes after the outbreaks, which reveals information about tourism equality. Thirdly, we offer comprehensive and national insights for the tourism sector and for stakeholders in order to provide targeted support for future tourism crises such as public health emergencies. As well, this offers timely knowledge for evidence-based decision-making for future waves and can guide equitable tourism recovery in the post-COVID-19 era.

Literature review

COVID-19 impacts on tourist mobility

Mobility is an important part of tourism (Shoval & Isaacson, 2007). Tourist mobility involves a sequence of the spatial movement of tourists (Hannam et al., 2014; Hardy et al., 2020), and is the key issue within tourism geographies (Lin et al., 2020). Understanding and modeling how tourist mobility in time and space plays an important role in tourism planning and management, such as the ways in which tourism facilities and routes design, tourism destination marketing, and management strategies (Zheng et al., 2022). The main topics in tourist mobility studies include monitoring and modeling spatio-temporal patterns and heterogeneity (Han et al., 2021; Liu et al., 2019), revealing factors that affect tourist movement and mobility (Henok, 2021; Jin et al., 2019), and predicting future tourist mobility trends (Mertzanis & Papastathopoulos, 2021; Zheng et al., 2017).

Tourist mobility is easily influenced by external political and crisis events (Jin et al., 2019; Zhou et al., 2021). At the beginning of the COVID-19 outbreak, researchers mainly captured how tourist mobility affected the spread of the virus because mobile people were regarded as potential vectors of viral transmission (Iaquinto, 2020). With COVID-19 continuing, a growing number of studies have explored how tourist behaviors have changed (i.e., tourism desire, travel behavior, consumption patterns) (Kock et al., 2020; Ren et al., 2022), and how these changes have been impacted by government-controlled policies (Collins-Kreiner & Ram, 2021; Zha et al., 2022) and tourists' psychological factors (Arbulú et al., 2021).

These studies can be divided into two mainstream categories according to the research paradigm: data-driven research, which highly relies on data availability and computational modeling, and explanatory research, which is designed for causal and mechanism analyses that identify the driving force behind tourist mobility and behavior changes. Most studies are based on statistics such as by using the government's official tourism statistics, one study compared the volume and structural changes of the flow of tourism in Finland and Estonia from 2019 to 2020 (Ivanov et al., 2021). Some studies have tried to use big data to monitor how COVID-19 has impacted tourist mobility behavior. For example, based on social media comment data using the travel contact trajectory and spatial trajectory approach, Gao et al. (2021) explored the changes in urban tourists' spatial behaviors before, during, and after the pandemic in Nanjing, China. Another study using Google Destination Insights data examined how moderating distance factors (i.e., geographic, cultural, economic, social, political) affected the relationship between COVID-19 cases and origin-destination countries' bilateral tourism demands (Yang et al., 2022).

Given that there are a collection of factors that influence tourist dynamics, unpacking the mechanism of COVID-19s impact on tourist mobility is a long-term challenge. Previous studies have mainly been based on related theories, such as travel risk perception (Neuburger & Egger, 2021) and tourist personalities (Morar et al., 2021), creating an empirical analysis of the determinant factors that might influence the tourist mobility response to the pandemic. One study used the tourist trust, travel constraint, and extended theory of planned behavior as a theoretical basis to explain the influence of travel promoting, restricting, and attitudinal factors on tourist travel decisions (Shin et al., 2022).

Data and tools used in tourist mobility studies

Previous studies on tourist mobility involve various types of data and spatial analysis methods (i.e., complex network, geoinformatics) (Kádár & Gede, 2021). Over the last few decades, tourism geography scholars have mainly used actively solicited tourists' travel behavior data, including, for example, the self-reported questionnaire survey data (Han et al., 2021), and GPS data requires that tourists carry GPS sensors during their travels (Liu et al., 2022). However, because tourist mobility information is collected via actively collected, these studies are restricted to relatively small samples and at the micro spatial scale (i.e., within a destination) (Domenech et al., 2020; Zheng et al., 2019). Additionally, statistical data have also been widely used in tourist mobility studies (Kulshrestha et al., 2020), but this data has had low temporal and spatial precision issues.

In recent years, the fast development of tracking and big data technologies (i.e., machine learning models) (Hardy & Aryal, 2020) have allowed us to obtain massive positioning information of tourists' travel behaviors (i.e., mobile phone signaling data, smart-card data, social media check-ins data) (Chen et al., 2021; Türk et al., 2021), attracting the greater interests of tourism geographers. These data are passively generated without the users' awareness instead of being actively collected like survey data (Schmücker & Reif, 2022). Mobile phone positioning data has the advantage of generating real-time information about tourists with high temporal and spatial resolution, such as who they are, where they visit, and when (Saluveer et al., 2020). This kind of data have been widely used in monitoring the spatial structures and patterns of tourist mobility (Park et al., 2020; Xu et al., 2021). These studies have greatly broadened our understanding of tourist mobility, but many studies have been inhibited by shortages in the availability of mobile phone positioning data, such as time precision and long-time series span, spatial scale, and coverage amounts. These studies have primarily been based on short-term temporal data (Kraemer et al., 2020; Tan et al., 2021) and cannot comprehensively assess the long-term changes occurring before and post-pandemic (Miao et al., 2021; Weaver, 2021; Xie et al., 2021).

Research gaps analysis

Based on the aforementioned literature, we identify the following gaps that we will address in this paper: Firstly, current studies on changes in tourist mobility after the COVID-19 outbreaks either use traditional data (i.e., statistic data, surveying data) or focus only on the early stage after the initial outbreak. It is necessary to understand the long-term changes of tourist mobility in order to bolster tourism recovery. More importantly, given the recurrence of the pandemic, establishing how multiple waves can affect tourist mobility is becoming more urgent. Nevertheless, current literature suggest that to date, such contributions are few due to the difficulty of data acquisition.

Secondly, it would be valuable for policymakers and stakeholders in crisis management to understand the socio-demographic disparities in tourist mobility changes after the outbreaks. While some studies have gained a glimpse of social-demographic gaps in tourist mobility by using questionnaire surveys, they are faced with issues of representation. Therefore, it is necessary to conduct a study using big data with demographic information.

Thirdly, even though we acknowledge that different cities have different responses to the public health crisis, there is a lack of empirical evidence regarding how these tourist mobility variations appear in diverse territorial contexts in response to COVID-19.

Fourthly, it is relatively underdeveloped for researchers by using a national scale daily mobility dataset to explore the long-term dynamics of tourist mobility after COVID-19, this provides constrained information about the nation's emergency management policy. In this vein, it is necessary to analyze how these changes differ between cities on a national scale to holistically identify the disparities of the pandemic in different cities.

Methods and data

Study methodology

Time series tourist mobility pattern cluster analysis. The time series cluster analysis helped us identify tourist mobility patterns using the daily number of tourists in each city. The cluster algorithm method is the K-means of the machine learning method, which is the distance measurement clustering algorithm of unusual scenic spots (Gibbs et al., 2020). Given a set of observations (x_1, x_2, …, x_n), where each observation is a d-dimensional real vector, K-means clustering aims to partition the n observations into k (≤ n) sets S = {S_1, S_2, …, S_k} to minimize the within-cluster sum of squares (i.e., variance). Formally, the objective is to find the Eq. (1). The K value was identified by the “Elbow method” (Eyre et al., 2020; Tian et al., 2019) and “Silhouette Coefficient” (Hie et al., 2019).

$$\underset{S}{argmin} \sum_{i=1}^{k} \sum_{x \in S_i} \left\| x - \mu_i \right\|^2 \tag{1}$$

Assessing the dynamic changes of tourists and the impact of COVID-19. In this study, the tourist change rate was constructed to measure the year-on-date tourist change percentage (i.e., 1st Jan 2020 vs. 1st Jan 2019) before and after the COVID-19 outbreaks. The year 2019 was defined as the base year to compare the difference between the first and second outbreak waves.

The tourist change rate was calculated using the following Eq. (2):

$$TCR_{y,d} = \frac{TN_{y,d} - TN_{2019,d}}{TN_{2019,d}} \times 100\% \tag{2}$$

where TCR is the number of tourist year-to-date change rates after COVID-19. For the pre-pandemic levels ratio, y is the year, d is the date, and TN is the number of tourists. When $TCR = 0$, the number of tourists is the same as at pre-pandemic levels; when $TCR > 0$, the number of tourists is higher than at pre-pandemic levels; when $TCR < 0$, the number of tourists fell below that of pre-pandemic levels.

The relationship of tourist change rates and city features in two waves.

$$\text{Model 1}: TCR_{wave1} = F\left(X^g, X^p, X^d, X^k\right)$$

$$\text{Model 2}: TCR_{wave2} = F\left(X^g, X^p, X^d, X^k\right)$$

where TCR is the tourist change rate function; X^g is the GDP per capita of the city; X^p is the population size; X^d is the distance to Beijing; X^k is the average daily COVID-19 cases; $F(\cdot)$ is the linear regression formulation.

Data description

Tourist data

We followed the United Nations World Tourism Organization's broad definition of 'tourist' in our study and defined a tourist "as a traveler taking a trip to the main destination outside his/her usual environment, for less than a year, for any main purpose (business, leisure or other personal purpose) other than to be employed by a resident entity in the country or place visited" (World tourism organization, 2008). In this study, we aggregate daily tourist mobility by the city of origin, which can be calculated from Beijing's total inflow of human mobility, minus non-tourism mobility (travel to work or a place of residence). Where total human mobility is extracted from the location of the mobile phone signaling base station. Work and place of residence are identified by the algorithm of the longest dwelling time during the day and night according to the time-constrained detection method (Vanhoof et al., 2018). Here is a sample of mobile data that belongs to the tourist in Table *S*9 of the Supplementary Data file.

The data are anonymized mobile phone data provided by a third party, China Unicom, which is one of the three major providers in China. By 2021, China Unicom had a market share of 19.26 % (China Mobile Annual Report, 2021; China Telecom Annual Report, 2021; China Unicom Annual Report, 2021). We obtained three years of data during the same period between Jan 1st and May 31st, from 2019 to 2021, and three variables of tourist behavior, including the daily number of tourist mobility, their age groups, and gender groups. To ensure anonymity, every piece of data must be grouped by at least 15 individuals in the database. The study used mobility data aggregated by city and only considered cities with at least 15 tourists per day. For our analysis, we derived the daily tourist data in 254 cities in mainland China.

Daily COVID-19 data

We mainly collected the historical daily number of confirmed cases and risk levels under the Hierarchical Containment Measures in each city. All these data were openly available on the official website of the National Health Commission of the People's Republic of China.

Others

Data used to identify the factors influencing tourist change rates in cities, such as population size and GDP per capita, are from the *China City Statistical Yearbook* (2020). The city data used in this study are from 2019, pre-COVID-19. Distances were measured from the central location of each city to the central location of Beijing.

Results

How did overall domestic tourist mobility change in response to COVID-19 during different outbreak waves?

Fig. 1a illustrates the main stages of the process following the first wave in 2020 and the second wave in 2021. Based on the daily number of tourist change trends, we divided the period after the initial COVID-19 outbreak into a downturn and the subsequent recovery stages, respectively. As the number of confirmed cases gradually decreased due to improvements in massive testing, contact tracing, and a series of effective control measures, many cities began relaxing travel restrictions and resumed their tourism businesses, with tourist mobility gradually reaching pre-pandemic levels (Fig. 1a). Fig. 1b shows the daily total number of domestic tourists in Beijing during the same months in a row over three years, from 2019 to 2021. From 2019 to 2021, the number of domestic tourists in Beijing witnessed a dramatic decline with a rate of 35.49 % in 2020 and a noticeable increase with a rate of 62.61 % in 2021. On average, the number of tourists showed a slight growth of 2.45 % during the same period.

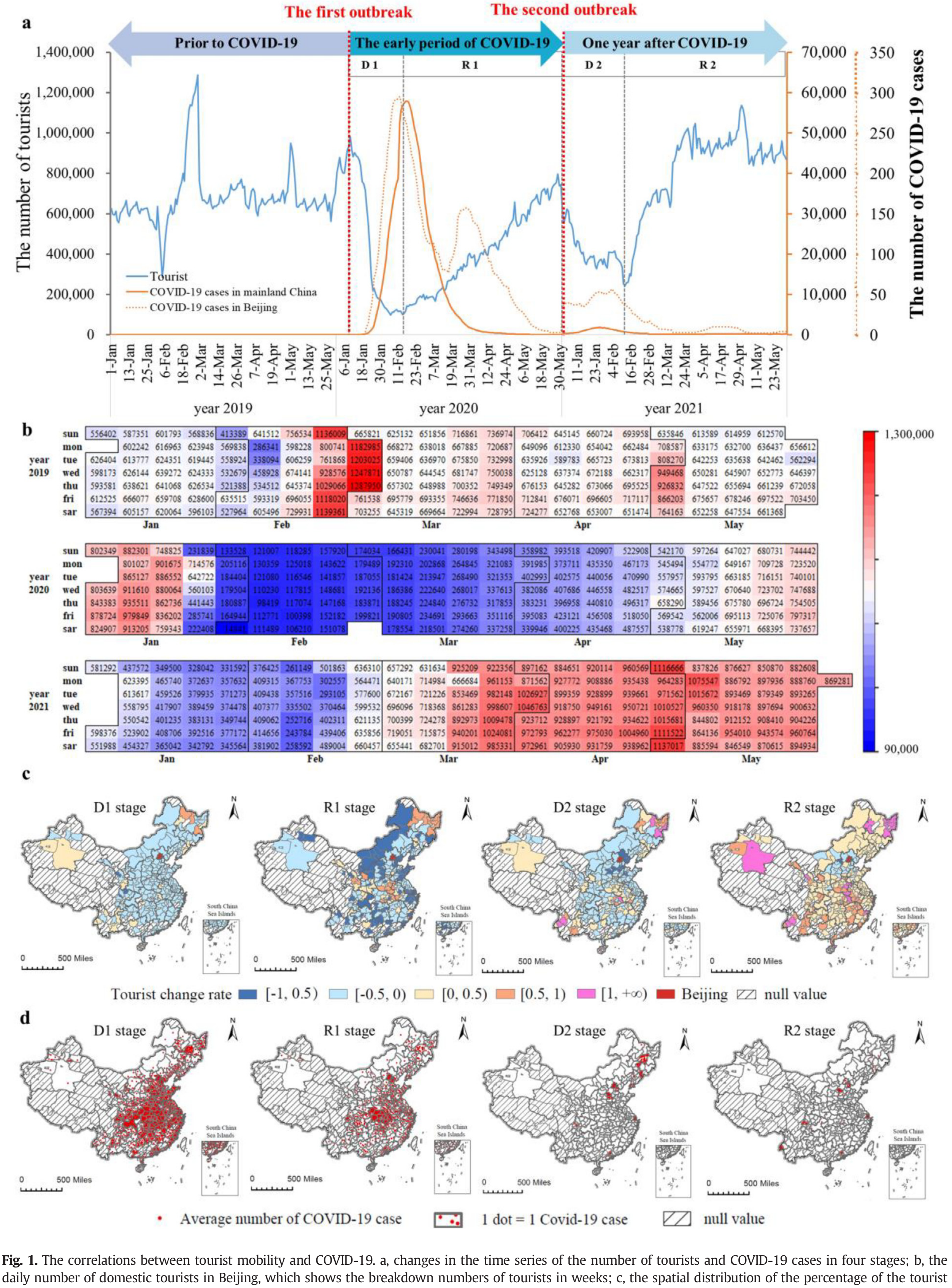

Fig. 1. The correlations between tourist mobility and COVID-19. a, changes in the time series of the number of tourists and COVID-19 cases in four stages; b, the daily number of domestic tourists in Beijing, which shows the breakdown numbers of tourists in weeks; c, the spatial distribution of the percentage of the tourist change rate for 254 cities during four stages; d, the spatial distribution of the average daily number of COVID-19 cases for 254 cities during four stages.

The maps in Fig. 1c and d show the year-to-date tourist change rate and its corresponding COVID-19 cases in pairs for 254 cities in four stages (see Tables S1, and S2 of Supplementary Data). We can see that a non-correlated relationship between the tourist change rate and confirmed cases in the origin cities in terms of tourist mobility.

By comparing the downturn stages of two waves - the downturn stage of the first wave (D1, from Jan 10th, 2020, to Feb 14th, 2020) and the downturn stage of the second wave (D2, from Jan 1st, 2021, to Feb 12th, 2021) - we found that the number of tourists in D1 declined more than in D2. The volume of tourists dropped sharply - around a 90 % decrease in the first wave and around a 70 % in the second wave compared to pre-pandemic levels. The relatively smaller percentage in the second wave is partly due to the precision and refined control policies by the central government that greatly reduced the impact of the pandemic on population mobility, such as intensive Hierarchical Containment Measures (HCMs) (National Health Commission of the People's Republic of China, 2021). The control area was also gradually narrowed down to specific residential communities and buildings. Recently, more precise control measures have emerged, such as the "Time and Space Companion" in November 2021, which uses big data to locate the possible contacts of potential virus carriers. The temporal resolution reached 10 min and space accuracy reached 800 m × 800 m.

By comparing the recovery stage of the first wave (R1, from Feb 15th, 2020, to May 31st, 2020) with the recovery stage of the second wave (R2, from Feb 13th, 2021 to May 31st, 2021), we found that the number of tourists in R2 recovered (106 days) faster than those in R1 (30 days) in terms of time spent rehabilitating themselves to pre-pandemic levels. Possible reasons for this improvement could be a) after a long-term decline in the tourism economy, policymakers and tourism practitioners enacted a series of strategies to expand domestic demand, leading to the fast-paced recovery of domestic tourism; or b) lessons were learned from the previous wave, and the government and stakeholders were better prepared both physically and psychologically. Notably, along with the introduction of vaccines after March 2021, the number of tourists had soared to 40 % higher than at pre-pandemic levels in 2019. This might be partially explained by the increasing number of people getting vaccinated and the irrational consumption activities of individuals after the virus hit.

How did tourist mobility changes vary among different socio-demographic tourists?

By gender

Since the categories of gender do not fit a normal distribution with 95 % confidence (see Table A3 in appendix), we chose nonparametric tests (De Biasi et al., 2020) to examine disparities in the gender categories in four stages. Fig. 2a and b illustrate how the number of tourists changed by gender during the two waves. Subplots a and b introduce similar trends observable in female and male groups during the downturn stages of the two waves (Table A4 shows no statistical differences between females and males for tourist change rate in the two decline stages). However, the trends differed during the recovery stages (Table A4 shows statistical differences between females and males for tourist change rate in the two increase stages). Females recovered more slowly than males during the first wave, whereas the opposite occurred during the second wave. During R1, the pandemic affected females more than males (the red line below the blue line), implying that it was more difficult for female tourists to recover to pre-pandemic levels after the first wave. During R2, both female and male groups recovered to pre-pandemic levels at the same time, whereas after they reached that level, female tourists recovered far better and faster (the red line went beyond the blue line).

By age

Since the categories of age do not conform to a normal distribution with 95 % confidence (see Table A5 in appendix), we used nonparametric tests to examine the disparities in the age categories in four stages. Fig. 2c and d illustrate how the number of tourists changed by age during the two waves. Subplot c introduces a severe issue of tourist loss for all groups in the first wave: a lower-than-normal level of tourists persisted for about four months (Table A6 shows no statistical differences between females and males for tourist change rate in the D1 stage). The lowest daily decrease in the ratio of tourist change rate reached around 80 % for the number of tourists. During the R1 stage, tourists aged 19 to 39 years old recovered relatively faster than other groups, and tourists over 50 and under 18 years old recovered at a relatively slower pace (Table A6 shows statistical differences between females and males for tourist change rate in the R1 stage). Subplot d shows that during the second wave, D2, those under 18 years old suffered the most serious stress, while those over 60 years old were the least affected (Table A6 shows statistical differences between females and males for tourist change rate in the D2 stage). During R2, tourists over 50 years old recovered relatively faster than other groups (Table A6 shows statistical differences between females and males for tourist change rate in the R2 stage).

A comparison of Fig. 2c and d reveals that, contrary to any intuitive projection, those most infected by COVID-19 in the first wave were the elderly tourists, whereas they suffered relatively lower rates, with the highest post-event recovery performance level occurring during the second wave. Control strategies such as the testing certificate and the "Health Quick Response code (HQR)[1]" used for accessing airport and tourist attractions, reinstated the elderly's lost travel accessibility during the first wave. Many government and public spaces are still actively trying to solve the problems faced by the elderly by using the HQR, such as the "Scan ID card[2]" and "Offline code.[3]" These measures alleviate the COVID-19 control measures that discriminated against the elderly during the second wave.

[1] The mobile internet-based "Health Quick Response Code" has played a crucial role in helping China control the pandemic and resume work, production, and businesses.

[2] "Scan ID card" means the elderly can check their "Health Quick Response Code" using a professional reading device.

[3] "Offline code" means the elderly can take a printed version of offline "Health Quick Response Code".

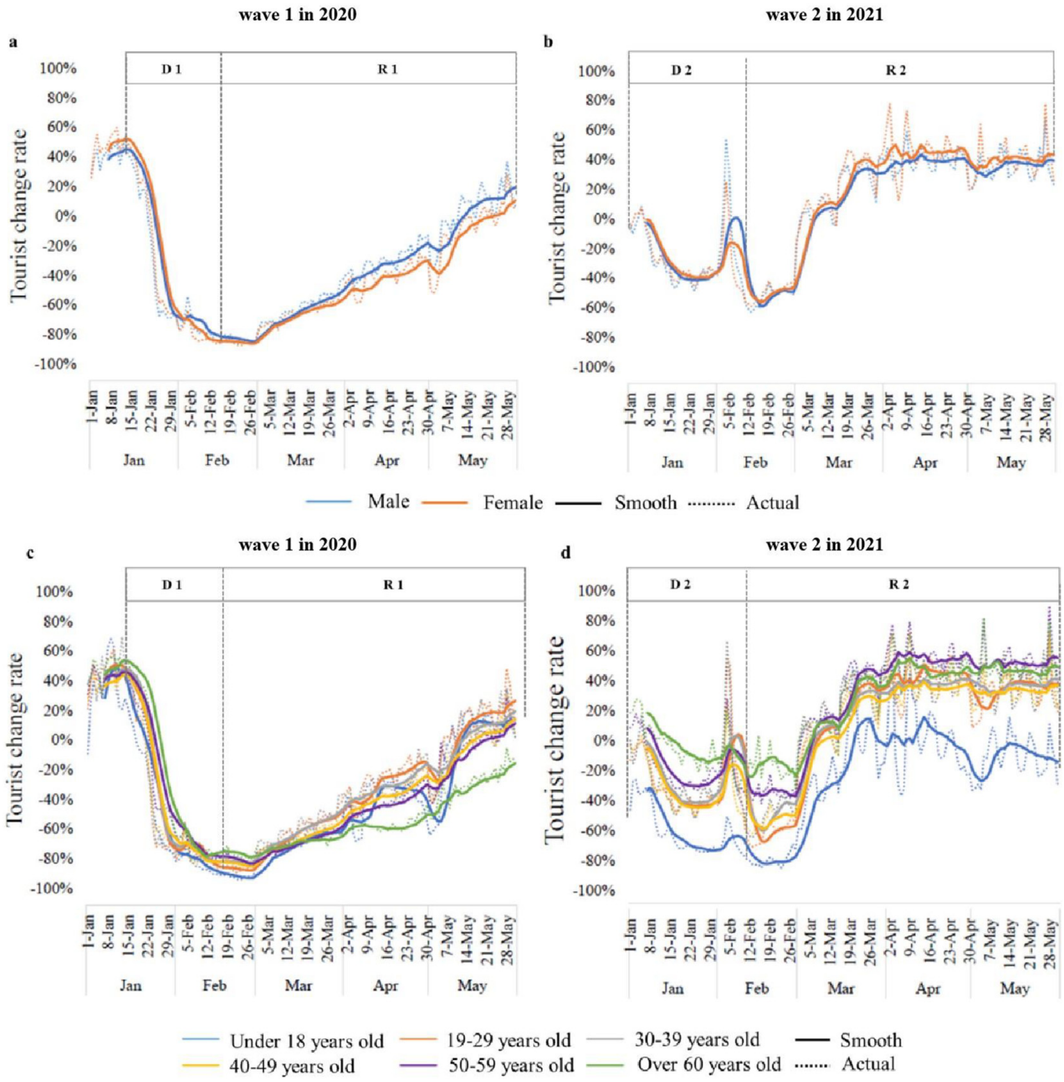

Fig. 2. The socio-demographic disparities in the tourist change rate. a, the tourist change rate compared with pre-pandemic levels measured by gender groups in the first wave; b, the tourist change rate compared with pre-pandemic levels measured by gender groups in the second wave; c, the tourist change rate compared with pre-pandemic levels measured by age groups in the first wave; d, the tourist change rate compared with pre-pandemic levels measured by age groups in the second wave. Note: The imaginary lines are the actual daily number of tourists. The solid line is the 7-day moving average. To filter the fluctuations between workdays and weekends, we conducted a 7-day moving average.

How did tourist mobility changes differ from one city to another?

The spatial variation in inter-city tourist mobility change remains largely unknown. Based on the time-series tourist change rate dynamics using the K-means cluster analysis method, we identified the tourist mobility change patterns at the city level. The K value was decided by using the "Elbow method" and "Silhouette Coefficient." In the first wave, as shown in Fig. A1 in the appendix, the K value of the elbow is 3 (the highest curvature), so the best K value for clustering this data set should be 3, and the silhouette score with three clusters is 0.487, which is relatively higher. In the second wave, as shown in Fig. A2, the K value of the elbow is 3 (the highest curvature), so the best K value for clustering this data set also should be 3, and the silhouette score with three clusters is 0.371, which is relatively higher. Finally, we decided on three kinds of tourist mobility change patterns in the first (Fig. 3a) and second waves (Fig. 3b).

Notably, in the fluctuation shown in Fig. 3c and d, the turning points of the lines were rather similar, but the fluctuation magnitudes were heterogeneous, which indicates that COVID-19 outbreaks have impacted cities at the same time, but in varying degrees. The cities from the pattern A cluster (such as Zhumadian; see the characteristics of these cities in Tables A7 and A8 in the appendix) displayed the quickest recovery and strongest increase ratio in tourist mobility; however, such cluster cities accounted for only 13.78 % in the first wave and 7.87 % in the second wave. The cities from the pattern C cluster (such as Shanghai; see the

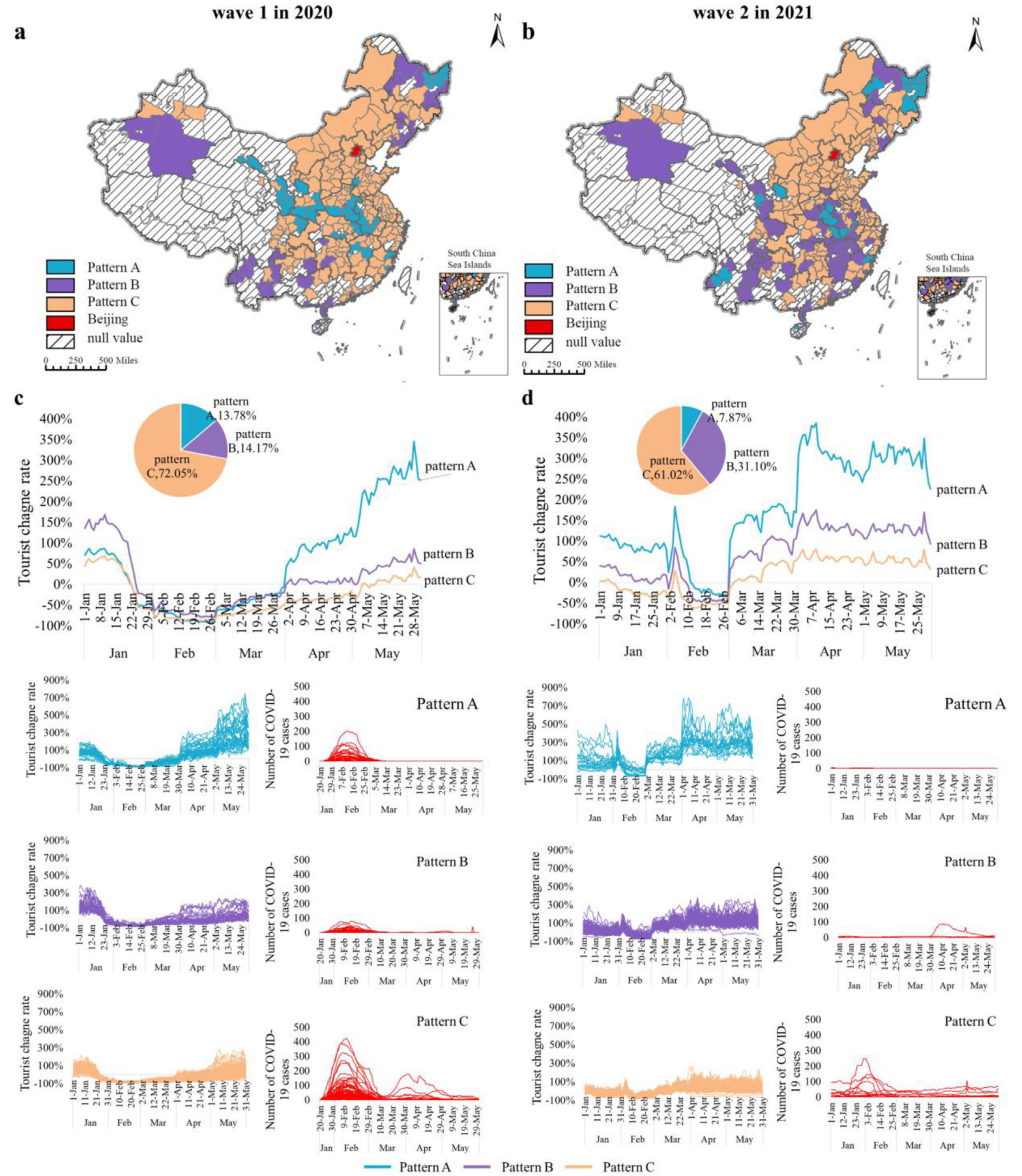

Fig. 3. Tourist mobility change patterns in response to the first wave of the outbreak in 2020, and the second wave of the outbreak in 2021. a, b, pattern map showing the spatial distribution of time-series clusters; c, d, tourist mobility change pattern clusters correspond with the daily COVID-19 cases in each city.

characteristics of these cities in Tables A7 and A8 in the appendix) suffered a relatively more severe hit in tourist mobility, which occupies a large proportion, with a ratio of 72.05 % in the first wave and 61.02 % in the second wave.

We then quantified how tourist mobility change patterns vary with the origin city's population size, economic development level, and distance to Beijing. Through correlation analysis (see Tables A9 and A10), the three clusters were significantly associated with the city's population size (first wave: $r = 0.180$, $p = 0.004$; second wave: $r = 0.191$, $p = 0.002$), GDP per capita (first wave: $r = 0.336$, $p < 0.001$; second wave: $r = 0.268$, $p < 0.001$), and distance to Beijing (first wave: $r = -0.162$, $p < 0.01$; second wave: $r = -0.338$, $p < 0.001$). As shown in Fig. 4a and b, we found that although pattern cluster cities were associated with their population size, economic development level, and distance to Beijing, there were also substantial spatial disparities in the two waves.

Firstly, there are obvious variations in the pandemic's effects on inter-city tourist travel between cities in terms of their geographical distance to Beijing. As shown in Fig. 4g, the tourist change rate was not association with distance during the first wave, which likely had a massive and widespread impact. Yet, during the second wave, as shown in Fig. 4h, the tourist change rate exhibits linear attenuation with the distance to Beijing. The closer city was hit hardest of all, while the city farthest away showed a relatively better increase rate. Tobler's first law of geography (Joo et al., 2017) may explain the aforementioned facts to some extent. Because geographical distance is a key determinant of the uneven spreading of the virus (Tsiotas & Tselios, 2022), cities nearest to Beijing may be more likely to be infected by the pandemic, leading to a wider-range outbreak. For instance, after the second wave, cities around Beijing such as Shijiazhuang were quickly infected by their proximity to the high-risk area. This aggravated the issue of tourists' travel behaviors in the vicinity of Beijing. The main COVID-19 pressure points have been in cities near Beijing, rather than being dispersed all over the country during the second wave.

Secondly, urban economic development levels were considered to be the main factor in determining their tourist travel possibilities. We referred to the GDP per capita of each city to compare the tourist change rate variations among them. We found that the tourist change rate depends nonlinearly on the GDP per capita. The higher the city's GDP per capita is, the lower their tourist change rate. Moreover, the correlative relationship between the city's GDP per capita and tourist change rate in the first wave ($p < 0.001$, $R2 = 0.235$, see model 1 in Table A11 of appendix) is more significant than in the second wave ($p = 0.012$, $R2 = 0.247$, see model 2 in Table A11 of appendix). As shown in Fig. 4c, the most developed and wealthy cities experienced the hardest pandemic shock in the first wave (most of the dots in the fourth quadrant are orange). In addition, as shown in Fig. 4c and d, both in the first and second waves, most tourists originating from poorer cities suffered a lower negative impact from the pandemic (most of the blue dots representing pattern A are located in the second quadrant). Both richer and poorer cities were hit hard,

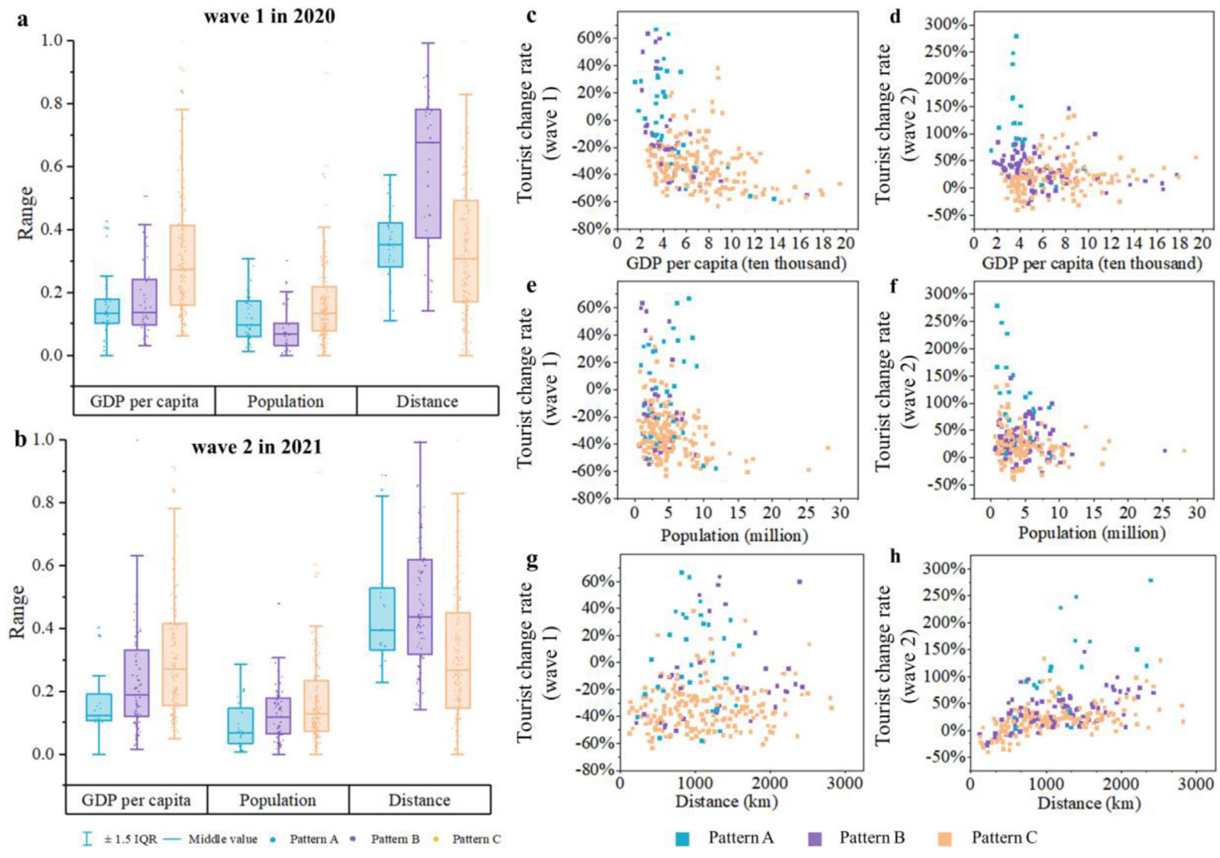

Fig. 4. Tourist mobility patterns in response to local-scale epidemic wave. Each dot represents a city in here and the coloring scheme is shared with Fig. 3. a, b, box plot of the characteristics of the city for tourist mobility patterns. All value scaling compressed to 0–1; c, d, quadrant analysis for addressing the tourist change rate in GDP per capita of the city, units are Chinese yuan; e, f, quadrant analysis for addressing the tourist change rate in the city's population size; g, h, quadrant analysis for addressing the tourist change rate in the city's distance to Beijing.

and the main differences were in the recovery speed and level. It is also evident that the recovery speed is inversely proportional to the maturity level of economic development.

Thirdly, urban population size was the key variable in measuring the volume of inter-city travel mobility. However, the correlation between tourist change rate and the city's population size was not always significant. The correlation was not significant in the first wave ($p < 0.190$, R2 = 0.235; see model 1 in Table A12 of appendix), but as shown in Fig. 4e, tourists in the largest cities suffered the most (in orange, which represents pattern C). While the correlation was negatively significant in the second wave ($p = 0.098$, R2 = 0.247; see model 2 in Table A13 of appendix), the best recovery-level cities were smaller (see Fig. 4f), showing that small cities can actually be more robust than larger ones. This may be because these cities usually have less human mobility, which, to some extent, may have protected them from the spread of the virus. Moreover, the number of tourists in those cities was relatively small during the previous year, so even a slight increase in tourists would lead to a large tourist change rate.

Discussion and conclusion

With the help of this long-term, wide-scale, high temporal resolution using highly reliable mobile phone data, this study contributes a comprehensive understanding of the dynamic changes in tourist mobility both before and post outbreak, and following the multiple waves. We observed that compared with the previous year's level, the number of domestic tourists in Beijing suffered a severe loss during 2020, then increased to even better than pre-pandemic levels one year after COVID-19. The number of domestic tourists in 2020 dropped sharply by 35.49 % compared with 2019. However, there was a slight average growth rate of 2.45 % from 2019 to 2021. Groups such as females and the elderly were more vulnerable during the first outbreak, whereas the opposite occurred during the second wave one year later. The same groups exhibited a relatively small external impact and recovered faster and more robustly than other groups, which demonstrates a distinct pattern of 'better-than-before' performance. Tourists under 18 years old suffered the most constant and serious impact of COVID-19. We also observed that the pandemic impacted cities simultaneously but to various degrees. This depended on the travel distance and socio-economic development of these cities, with larger, wealthier cities suffering from the most severe hit of all.

This study's findings are discussed in the following ways. Firstly, given that the tourism sector was severely hit by the pandemic over the past two years (Chica et al., 2021; United Nations News, 2021; World Tourism Organization, 2021), many studies are pessimistic about tourism's recovery (Fotiadis et al., 2021). Here, we demonstrated the new situation for Beijing, China, where the number of domestic tourists in the post-pandemic time was substantially greater than in the pre-pandemic stage, which could partly be explained by the strong international travel restrictions promoting domestic tourist mobility recovery (Yang et al., 2021). This means that the rapid increase in the number of tourists may have originated due to the substantial decrease in outbound international travel during the outbreaks. For example, tourists preferring international travel may choose domestic tourist destinations instead (Organisation for Economic Co-operation and Development, 2020). This result highlights the strong resilience and potential for domestic tourism to bolster economic recovery in the post-pandemic era (World Tourism Organization, 2020), especially for major cities in populated countries. If the global pandemic persists, these changes may have far-reaching consequences for the future development of tourism as a whole.

Secondly, recognizing tourist segmentation features is a fundamental issue in tourism research. Our results revealed that while the COVID-19 impact on tourist mobility varies for different socio-demographic subgroups, there were also substantial disparities during the two waves. We found that the elderly and female groups, which are normally recognized as vulnerable groups, were particularly affected by slow recovery speeds during the first wave. While their abilities to fight off the pandemic were limited in the first outbreak, during the second wave in the following year, these groups showed a relatively strong and faster recovery in terms of tourism-related activities. This might be explained by the fact that COVID-19s impact on tourist mobility was derived from external factors (i.e., travel restrictions of government strategies) and the internal psychology of spontaneous behavior (i.e., fear of contagion).

The gender disparities might be explained by the shift in female tourists' health risk perceptions (Neuburger & Egger, 2021) after the two waves. Our findings supported the previous studies that female tourists tended to be more sensitive to external disturbances after the first outbreak (Bhopal & Bhopal, 2020). However, one year after the pandemic, female tourists got used to the crisis and their risk perception gradually fell. This, coupled with suppressed tourist demands, led to massively increased tourist mobility after the second outbreak.

The difference in the elderly tourist mobility response between the first and second waves demonstrated high capabilities of 'coping' and 'learning from the past.' Previous studies indicated that access to information and the ability to respond to said information were associated with the subjective probability of risk preferences (Weill et al., 2020). Even if the elderly had lower risk perception due to their limited contact with the internet to access crisis information (Qiu et al., 2020), they were directly or indirectly constrained by government policies and restrictions in many ways during the early stage, such as the inability to show their "Health Quick Response code (HQR)" using a smartphone. With the help of family members and related organizations (i.e., the National health and wellness commission, and the National office for aging) facilitating "smart help for the elderly," more and more elderly people have improved their ability to use a smartphone (Xinhua News, 2022).

Thirdly, young people under 18 found it harder to recover to pre-pandemic levels, which might be explained by the fact that in mainland China, COVID-19 vaccinations were initially implemented for adults over 18 years old, and were not offered to those under 18 during our study period (Zheng et al., 2021). The latest research and media reports suggest that although vaccinations were offered to individuals under 18 after our observation period, their actual vaccination rate was very small (Bramer et al., 2020). This might be primarily because of "vaccine hesitancy," as many parents were concerned about the possible complications of vaccines and their unclear explanations for youngsters (Bell et al., 2020). This implies a relatively negative post-pandemic performance for tourists under 18, suggesting that the effects of the crisis are likely to persist for young people.

Finally, our study indicated that tourists originating from larger and richer cities suffered more due to the pandemic. As populated cities have been the main contributors to domestic tourism in Beijing, the high tourist decrease rate implies a very serious gap in the number of tourists in these cities. In contrast, the number of tourists originating from small cities suffered lower losses. In addition, we found that the tourist change ratewas not associated with distance during the first wave, which might be explained by the stronger and almost national impact of the pandemic during the first wave. However, during the second wave, the tourist change rate exhibited linear performance with the distance to Beijing; the largest tourist decline rate was more likely to happen as the remote cities performed better. It may be inferred that in the case of the second local outbreak, the associated restrictions, policies, and government surveillance on tourist mobility were generally stricter for the surrounding cities due to a higher-perceived contagion risk, which induced the highest decline in short-radius mobility around the city.

Our findings could provide several practical implications to promote the sustainable development of tourism in the post-pandemic era as follows:

(1) Given the overall growth of current domestic tourism after the outbreaks and during current weak tourism investments, we suggest and call for the government and stakeholders to strengthen investment in local tourism and provide strong support for the merger and recombination of the tourism industry in the next few years (Pham et al., 2021). This will not only meet tourists' needs and desires for travel, but can also encourage the benefits of tourism to spill over to other sectors.
(2) As the pandemic hit tourism mobility disproportionally in different demographic groups, this inspires us to rethink the issue of travel fair (Alarcón & Cole, 2019) and guide tourism toward an equitable recovery (Rastegar et al., 2021). Based on the data in our study, the impacts of the pandemic were larger in vulnerable groups, so special care for disadvantaged groups would narrow down the inequity that COVID-19 caused. If this issue is not fully resolved, the tourism industry might lose a large number of tourist markets during the recovery process, causing greater social and well-being inequalities.
(3) Our findings imply that the loss rate in the number of tourists was greater in larger and richer cities, which might help allocate more investment and offer prioritization policies for tourist markets in those major cities. Governments are supposed to allow some flexibility on control measurements (Bouman et al., 2021) rather than a "one-size-fits-all" solution. For example, each city should have a specific control policy and tourism recovery plan to better promote the balanced recovery of the different cities.
(4) We did not find a correlative relationship between tourist change rates and COVID-19 confirmed cases after the outbreaks by using mobile phone data from China. Despite mobility restrictions being one of the most common strategies to combat the virus spreading (Schlosser et al., 2020), it is necessary to reexamine the effectiveness of government travel restrictions and policies to avoid the spread of the virus, given the huge economic losses and consequences. Additionally, new evidence revealed from our analysis confirms that under the premise of effective pandemic control (i.e., offering vaccination, testing) (Aleta et al., 2020; Russell & Greenwood, 2021) and gradually precise control measures (i.e., China's National top-down Hierarchical Containment policy) (National Health Commission of the People's Republic of China, 2021), it is possible to restore domestic tourism and even accelerate its growth (Iaquinto, 2020). Therefore, there is a need for some new and more precise strategies to seek balance between tourist economics and tourist mobility. For example, related management sectors in tourist destinations have implemented strategies to increase social distancing and avoid overcrowding in places.
(5) As demonstrated in our findings, there were substantial disparities during the two waves. Pandemic prevention policies and tourist mobility management measures are meant to be gradual processes that opportunely adjust according to the wave features with different social-demographic subgroups. In addition, we suggest putting balanced recovery and equality development at the core of related control policies and the tourism recovery plan, instead of narrowly focusing on the number of tourist recoveries.
(6) Our findings imply that the tourist mobility change differentiates across cities and varies with the city's population size, economic development level, and geographical distance to Beijing. As well, the social-demographic disparities in tourist mobility have not previously been fully captured in tourist modeling. Researchers should be aware of such heterogeneity and disparities in their model assumptions when developing tourist mobility models to further study the effects of COVID-19.

We acknowledge that a major limitation in this paper is that our research used Beijing as its case study due to the limitation of data availability, which has specific characteristics regarding what measures to take when dealing with the pandemic. Therefore, we suggest that care be taken when generalizing our results. In addition, in big data studies, it is common to suffer from unbalanced observation issues. This is also a very cutting-edge research question in statistical analysis that we cannot address by ourselves. However, we believe the representativeness of our data is relatively high in the context of China. A research report on internet usage of underage residents in China during 2020 shows that the proportion of those under 18 years old who own mobile phones accounts for 65 % (China Internet Network Information Center, 2021). For future studies, researchers should be aware of tourism equity issues that have garnered a lot of interest in recent years (Rastegar et al., 2021) and should conduct a deep investigation to capture the inequities related to tourist mobility in the post-COVID-19 context. As well, according to UNWTO predictions (World Tourism Organization, 2022b), global tourism will recover to pre-pandemic levels by 2024 or later. International tourism's future recovery could lead to a new hypothesis regarding whether or not domestic tourism will decline due to the effects of the recovering number of people traveling internationally.

CRediT authorship contribution statement

Ling Yu: Conceptualization, Methodology, Writing – original draft, Visualization. **Pengjun Zhao:** Supervision, Writing – review & editing, Funding acquisition. **Junqing Tang:** Writing – review & editing. **Liang Pang:** Data curation.

Data availability

Source information and data to reproduce figures of this study are attached as a separate file in Supplementary Data.

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.

Acknowledgments

We are grateful for the constructive comments from the editors as well as the reviewers. This study was supported by National Natural Science Foundation of China (Grant numbers: 41925003, 42130402), and Guangdong Provincial Natural Science Foundation (Grant number: 2022A1515010696).

Appendix A. Supplementary data

Appendix and supplementary data to this article can be found online at https://doi.org/10.1016/j.annals.2022.103522.

References

Alarcón, D. M., & Cole, S. (2019). No sustainability for tourism without gender equality. *Journal of Sustainable Tourism*, *27*(7), 903–919.
Aleta, A., Martin-Corral, D., Pastore y Piontti, A., Ajelli, M., Litvinova, M., Chinazzi, M., ... Moreno, Y. (2020). Modelling the impact of testing, contact tracing and household quarantine on second waves of COVID-19. *Nature Human Behaviour*, *4*(9), 964–971.
Arbulú, I., Razumova, M., Rey-Maquieira, J., & Sastre, F. (2021). Can domestic tourism relieve the COVID-19 tourist industry crisis? The case of Spain. *Journal of Destination Marketing & Management*, *20*, Article 100568.
Bell, S., Clarke, R., Mounier-Jack, S., Walker, J. L., & Paterson, P. (2020). Parents' and guardians' views on the acceptability of a future COVID-19 vaccine: A multi-methods study in England. *Vaccine*, *38*(49), 7789–7798.
Bhopal, S. S., & Bhopal, R. (2020). Sex differential in COVID-19 mortality varies markedly by age. *The Lancet*, *396*(10250), 532–533.
Bouman, T., Steg, L., & Dietz, T. (2021). Insights from early COVID-19 responses about promoting sustainable action. *Nature Sustainability*, *4*(3), 194–200.
Bramer, C. A., Kimmins, L. M., Swanson, R., Kuo, J., Vranesich, P., Jacques-Carroll, L. A., & Shen, A. K. (2020). Decline in child vaccination coverage during the COVID-19 pandemic—Michigan care improvement registry, May 2016–May 2020. *American Journal of Transplantation*, *20*(7), 1930.
Callaway, E. (2021). Heavily mutated omicron variant puts scientists on alert. *Nature*, *600*(7887), 21.
Chen, J., Becken, S., & Stantic, B. (2021). Using Weibo to track global mobility of Chinese visitors. *Annals of Tourism Research*, *89(C*.
Chica, M., Hernández, J. M., & Bulchand-Gidumal, J. (2021). A collective risk dilemma for tourism restrictions under the COVID-19 context. *Scientific Reports*, *11*(1), 1–12.
China Internet Network Information Center (2021, July 20). Research Report on Internet Usage of Under-age in China in 2020. http://www.cnnic.cn/hlwfzyj/hlwxzbg/qsnbg/202107/t20210720_71505.htm.
China Mobile (2021). *(2022, March). China Mobile Annual Report.*
China Telecom (2021). *(2022, March). Annual Report.*
China Unicom (2021). *(2022, March). China Unicom Annual Report.*
Collins-Kreiner, N., & Ram, Y. (2021). National tourism strategies during the Covid-19 pandemic. *Annals of Tourism Research*, *89*, Article 103076.
De Biasi, S., Meschiari, M., Gibellini, L., Bellinazzi, C., Borella, R., Fidanza, L., ... Cossarizza, A. (2020). Marked T cell activation, senescence, exhaustion and skewing towards TH17 in patients with COVID-19 pneumonia. *Nature Communications*, *11*(1), 1–17.
Domenech, A., Gutierrez, A., & Clavé, S. A. (2020). Built environment and urban cruise tourists' mobility. *Annals of Tourism Research*, *81*, Article 102889.
Eyre, R., De Luca, F., & Simini, F. (2020). Social media usage reveals recovery of small businesses after natural hazard events. *Nature Communications*, *11*(1), 1–10.
Fotiadis, A., Polyzos, S., & Huan, T. C. T. (2021). The good, the bad and the ugly on COVID-19 tourism recovery. *Annals of Tourism Research*, *87*, Article 103117.
Gao, Y., Sun, D., & Zhang, J. (2021). Study on the impact of the COVID-19 pandemic on the spatial behavior of urban tourists based on commentary big data: A case study of Nanjing, China. *ISPRS International Journal of Geo-Information*, *10*(10), 678.
Gibbs, H., Liu, Y., Pearson, C. A., Jarvis, C. I., Grundy, C., Quilty, B. J., ... Eggo, R. M. (2020). Changing travel patterns in China during the early stages of the COVID-19 pandemic. *Nature Communications*, *11*(1), 1–9.
Gössling, S., Scott, D., & Hall, C. M. (2020). Pandemics, tourism and global change: A rapid assessment of COVID-19. *Journal of Sustainable Tourism*, *29*(1), 1–20.
Guerriero, C., Haines, A., & Pagano, M. (2020). Health and sustainability in post-pandemic economic policies. *Nature Sustainability*, *3*(7), 494–496.
Han, Y., Yang, G., & Zhang, T. (2021). Spatial-temporal response patterns of tourist flow under entrance tourist flow control scheme. *Tourism Management*, *83*, Article 104246.
Hannam, K., Butler, G., & Paris, C. M. (2014). Developments and key issues in tourism mobilities. *Annals of Tourism Research*, *44*, 171–185.
Hardy, A., & Aryal, J. (2020). Using innovations to understand tourist mobility in national parks. *Journal of Sustainable Tourism*, *28*(2), 263–283.
Hardy, A., Birenboim, A., & Wells, M. (2020). Using geoinformatics to assess tourist dispersal at the state level. *Annals of Tourism Research*, *82*, Article 102903.
He, L. Y., Li, H., Bi, J. W., Yang, J. J., & Zhou, Q. (2022). The impact of public health emergencies on hotel demand-estimation from a new foresight perspective on the COVID-19. *Annals of Tourism Research*, *94*, Article 103402.
Henok, B. G. (2021). Factors determining international tourist flow to tourism destinations: A systematic review. *Journal of Hospitality Management and Tourism*, *12*(1), 9–17.
Hie, B., Bryson, B., & Berger, B. (2019). Efficient integration of heterogeneous single-cell transcriptomes using Scanorama. *Nature Biotechnology*, *37*(6), 685–691.
Huang, X., Lu, J., Gao, S., Wang, S., Liu, Z., & Wei, H. (2022). Staying at home is a privilege: Evidence from fine-grained mobile phone location data in the United States during the COVID-19 pandemic. *Annals of the American Association of Geographers*, *112*(1), 286–305.
Iaquinto, B. L. (2020). Tourist as vector: Viral mobilities of COVID-19. *Dialogues in Human Geography*, *10*(2), 174–177.

Ivanov, I. A., Golomidova, E. S., & Terenina, N. K. (2021). Influence of the COVID-19 pandemic on the change in volume and spatial structure of the tourist flow in Finland and Estonia in 2020. *Regional Research of Russia*, *11*(3), 361–366.
Jin, X. C., Qu, M., & Bao, J. (2019). Impact of crisis events on Chinese outbound tourist flow: A framework for post-events growth. *Tourism Management*, *74*, 334–344.
Joo, D., Woosnam, K. M., Shafer, C. S., Scott, D., & An, S. (2017). Considering Tobler's first law of geography in a tourism context. *Tourism Management*, *62*, 350–359.
Kádár, B., & Gede, M. (2021). Tourism flows in large-scale destination systems. *Annals of Tourism Research*, *87*, Article 103113.
Kar, A., Le, H. T., & Miller, H. J. (2021). What is essential travel? Socioeconomic differences in travel demand in Columbus, Ohio, during the COVID-19 lockdown. *Annals of the American Association of Geographers* (pp. 1–24).
Kock, F., Nørfelt, A., Josiassen, A., Assaf, A. G., & Tsionas, M. G. (2020). Understanding the COVID-19 tourist psyche: The evolutionary tourism paradigm. *Annals of Tourism Research*, *85*, Article 103053.
Kraemer, M. U., Sadilek, A., Zhang, Q., Marchal, N. A., Tuli, G., Cohn, E. L., ... Brownstein, J. S. (2020). Mapping global variation in human mobility. *Nature Human Behaviour*, *4*(8), 800–810.
Kulshrestha, A., Krishnaswamy, V., & Sharma, M. (2020). Bayesian BILSTM approach for tourism demand forecasting. *Annals of Tourism Research*, *83*, Article 102925.
Lenzen, M., Sun, Y. Y., Faturay, F., Ting, Y. P., Geschke, A., & Malik, A. (2018). The carbon footprint of global tourism. *Nature Climate Change*, *8*(6), 522–528.
Levin, R., Chao, D. L., Wenger, E. A., & Proctor, J. L. (2021). Insights into population behavior during the COVID-19 pandemic from cell phone mobility data and manifold learning. *Nature Computational Science*, *1*(9), 588–597.
Lin, J., Cui, Q., Xu, H., & Guia, J. (2020). Health and local food consumption in cross-cultural tourism mobility: An assemblage approach. *Tourism Geographies*, 1–19.
Liu, P., Zhang, H., Zhang, J., Sun, Y., & Qiu, M. (2019). Spatial-temporal response patterns of tourist flow under impulse pre-trip information search: From online to arrival. *Tourism Management*, *73*, 105–114.
Liu, W., Wang, B., Yang, Y., Mou, N., Zheng, Y., Zhang, L., & Yang, T. (2022). Cluster analysis of microscopic spatio-temporal patterns of tourists' movement behaviors in mountainous scenic areas using open GPS-trajectory data. *Tourism Management*, *93*, Article 104614.
Matsuura, T., & Saito, H. (2022). The COVID-19 pandemic and domestic travel subsidies. *Annals of Tourism Research*, *92*, Article 103326.
Mertzanis, C., & Papastathopoulos, A. (2021). Epidemiological susceptibility risk and tourist flows around the world. *Annals of Tourism Research*, *86*, Article 103095.
Miao, L., Im, J., Fu, X., Kim, H., & Zhang, Y. E. (2021). Proximal and distal post-COVID travel behavior. *Annals of Tourism Research*, *88*, Article 103159.
Ministry of Culture and tTourism of the People''s Republic of China (2020, March 10). Basic situation of tourism market in 2019. https://www.mct.gov.cn/whzx/whyw/202003/t20200310_851786.htm.
Morar, C., Tiba, A., Basarin, B., Vujičić, M., Valjarević, A., Niemets, L., ... Lukić, T. (2021). Predictors of changes in travel behavior during the COVID-19 pandemic: The role of tourists' personalities. *International Journal of Environmental Research and Public Health*, *18*(21), 11169.
National Health Commission of the People''s Republic of China (2021, February 21). New Coronavirus Pneumonia Prevention and Control Plan (Fifth Edition). http://www.gov.cn/zhengce/zhengceku/2020-02/22/content_5482010.htm.
Neuburger, L., & Egger, R. (2021). Travel risk perception and travel behaviour during the COVID-19 pandemic 2020: A case study of the DACH region. *Current Issues in Tourism*, *24*(7), 1003–1016.
Organisation for Economic Co-operation and Development (2020, June 2). Tourism Policy Responses to the coronavirus (COVID-19). https://www.oecd.org/coronavirus/policy-responses/tourism-policy-responses-to-the-coronavirus-covid-19-6466aa20/#p-d1e27.
Park, S., Xu, Y., Jiang, L., Chen, Z., & Huang, S. (2020). Spatial structures of tourism destinations: A trajectory data mining approach leveraging mobile big data. *Annals of Tourism Research*, *84*, Article 102973.
Pham, T. D., Dwyer, L., Su, J. J., & Ngo, T. (2021). COVID-19 impacts of inbound tourism on Australian economy. *Annals of Tourism Research*, *88*, Article 103179.
Qiu, R. T., Park, J., Li, S., & Song, H. (2020). Social costs of tourism during the COVID-19 pandemic. *Annals of Tourism Research*, *84*, Article 102994.
Rastegar, R., Higgins-Desbiolles, F., & Ruhanen, L. (2021). COVID-19 and a justice framework to guide tourism recovery. *Annals of Tourism Research*, *91*, Article 103161.
Ren, M., Park, S., Xu, Y., Huang, X., Zou, L., Wong, M. S., & Koh, S. Y. (2022). Impact of the COVID-19 pandemic on travel behavior: A case study of domestic inbound travelers in Jeju, Korea. *Tourism Management*, *92*, Article 104533.
Russell, F. M., & Greenwood, B. (2021). Who should be prioritised for COVID-19 vaccination? *Human Vaccines & Immunotherapeutics*, *17*(5), 1317–1321.
Saluveer, E., Raun, J., Tiru, M., Altin, L., Kroon, J., Snitsarenko, T., ... Silm, S. (2020). Methodological framework for producing national tourism statistics from mobile positioning data. *Annals of Tourism Research*, *81*, Article 102895.
Schlosser, F., Maier, B. F., Jack, O., Hinrichs, D., Zachariae, A., & Brockmann, D. (2020). COVID-19 lockdown induces disease-mitigating structural changes in mobility networks. *Proceedings of the National Academy of Sciences*, *117*(52), 32883–32890.
Schmücker, D., & Reif, J. (2022). Measuring tourism with big data? Empirical insights from comparing passive GPS data and passive mobile data. *Annals of Tourism Research Empirical Insights*, *3*(2), Article 100061.
Sharma, A., Shin, H., Santa-María, M. J., & Nicolau, J. L. (2021). Hotels' COVID-19 innovation and performance. *Annals of Tourism Research*, *88*, Article 103180.
Shin, H., Nicolau, J. L., Kang, J., Sharma, A., & Lee, H. (2022). Travel decision determinants during and after COVID-19: The role of tourist trust, travel constraints, and attitudinal factors. *Tourism Management*, *88*, Article 104428.
Shoval, N., & Isaacson, M. (2007). Tracking tourists in the digital age. *Annals of Tourism Research*, *34*(1), 141–159.
Tan, S., Lai, S., Fang, F., Cao, Z., Sai, B., Song, B., Dai B., Guo, S., Liu, C., Cai, M., Wang, T., Wang, M., Li, J., Chen S., Qin, S., Floyd, J. R., Cao, Z., Tan, J., Sun, X., Zhou, T., Zhang, W., Tatem, A. J., Holme, P., Chen, X., & Lu, X. (2021). Mobility in China, 2020: A tale of four phases. National Science Review, 8(11), nwab148.
Tian, T., Wan, J., Song, Q., & Wei, Z. (2019). Clustering single-cell RNA-seq data with a model-based deep learning approach. *Nature Machine Intelligence*, *1*(4), 191–198.
Tsiotas, D., & Tselios, V. (2022). Understanding the uneven spread of COVID-19 in the context of the global interconnected economy. *Scientific Reports*, *12*(1), 1–15.
Türk, U., Östh, J., Kourtit, K., & Nijkamp, P. (2021). The path of least resistance explaining tourist mobility patterns in destination areas using Airbnb data. *Journal of Transport Geography*, *94*, Article 103130.
Uglis, J., Jęczmyk, A., Zawadka, J., Wojcieszak-Zbierska, M. M., & Pszczoła, M. (2022). Impact of the COVID-19 pandemic on tourist plans: A case study from Poland. *Current Issues in Tourism*, *25*(3), 405–420.
United Nations News (2021, November 29). The COVID-19 epidemic will cost the global tourism industry $2 trillion this year. https://news.un.org/zh/story/2021/11/1095142.
Vanhoof, M., Reis, F., Ploetz, T., & Smoreda, Z. (2018). Assessing the quality of home detection from mobile phone data for official statistics. *Journal of Official Statistics*, *34*(4), 935–960.
Weaver, A. (2021). Tourism, big data, and a crisis of analysis. *Annals of Tourism Research*, *88*, Article 103158.
Weill, J. A., Stigler, M., Deschenes, O., & Springborn, M. R. (2020). Social distancing responses to COVID-19 emergency declarations strongly differentiated by income. *Proceedings of the National Academy of Sciences*, *117*(33), 19658–19660.
World Tourism Organization (2008). Glossary of tourism terms. https://www.unwto.org/glossary-tourism-terms.
World Tourism Organization (2020, September 14). UNWTO highlights potential of domestic tourism to help drive economic recovery in destinations worldwide. https://www.unwto.org/news/unwto-highlights-potential-of-domestic-tourism-to-help-drive-economic-recovery-in-destinations-worldwide.
World Tourism Organization (2021, January 28). 2020: Worst year in tourism history with 1 billion fewer international arrivals. https://www.unwto.org/news/2020-worst-year-in-tourism-history-with-1-billion-fewer-international-arrivals.
World Tourism Organization (2022, January 29a). Tourism in the 2030 agenda. https://www.unwto.org/tourism-in-2030-agenda.
World Tourism Organization (2022, January 18b). Tourism grows 4% in 2021 but remains far below pre-pandemic levels. https://www.unwto.org/taxonomy/term/347.
Xie, G., Qian, Y., & Wang, S. (2021). Forecasting Chinese cruise tourism demand with big data: An optimized machine learning approach. *Tourism Management*, *82*, Article 104208.
Xinhua News (2022, Jun 16). Carry out the "wisdom to help the elderly" action. http://www.gov.cn/xinwen/2022-06/16/content_5696072.htm.
Xu, Y., Li, J., Belyi, A., & Park, S. (2021). Characterizing destination networks through mobility traces of international tourists—A case study using a nationwide mobile positioning dataset. *Tourism Management*, *82*, Article 104195.
Yang, Y., Altschuler, B., Liang, Z., & Li, X. R. (2021). Monitoring the global COVID-19 impact on tourism: The COVID19tourism index. *Annals of Tourism Research*, *90*, Article 103120.

Yang, Y., Zhang, L., Wu, L., & Li, Z. (2022). Does distance still matter? Moderating effects of distance measures on the relationship between pandemic severity and bilateral tourism demand. *Journal of Travel Research*. https://doi.org/10.1177/00472875221077978.

Zha, J., Tan, T., Ma, S., He, L., & Filimonau, V. (2022). Exploring tourist opinion expression on COVID-19 and policy response to the pandemic's occurrence through a content analysis of an online petition platform. *Current Issues in Tourism*, *25*(2), 261–286.

Zheng, W., Huang, X., & Li, Y. (2017). Understanding the tourist mobility using GPS: Where is the next place? *Tourism Management*, *59*, 267–280.

Zheng, W., Li, M., Lin, Z., & Zhang, Y. (2022). Leveraging tourist trajectory data for effective destination planning and management: A new heuristic approach. *Tourism Management*, *89*, Article 104437.

Zheng, W., Yan, X., Zhao, Z., Yang, J., & Yu, H. (2021). COVID-19 vaccination program in the mainland of China: A subnational descriptive analysis on target population size and current progress. *Infectious Diseases of Poverty*, *10*(1), 1–10.

Zheng, W., Zhou, R., Zhang, Z., Zhong, Y., Wang, S., Wei, Z., & Ji, H. (2019). Understanding the tourist mobility using GPS: How similar are the tourists? *Tourism Management*, *71*, 54–66.

Zhou, B., Zhang, Y., & Zhou, P. (2021). Multilateral political effects on outbound tourism. *Annals of Tourism Research*, *88*, Article 103184.