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## How did human dwelling and working intensity change over different stages of COVID-19 in Beijing?

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## ABSTRACT

The COVID-19 pandemic has changed human daily activities significantly. Understanding the nature, causes, and extent of these changes is essential to evaluate the pandemic's influence on commerce, transportation, employment, and environment, among others. However, existing studies mainly focus on changes to general human mobility patterns; few have investigated changes in specific human daily activities. Based on one-year longitudinal mobile phone positioning data for more than 31 million users in Beijing, we tracked intensity changes in two basic human daily activities, dwelling and working, over the stages of COVID-19. The results show that during COVID-19 outbreak, human working intensity decreased about 60% citywide, while dwelling intensity decreased about 40% in some work and education areas. After COVID-19 was under control, intensity in most regions has recovered, but that in schools, hotels, entertainment venues, and tourism areas has not. These intensity changes at regional scale are due to behavior changes at individual scale: about 43% of residents left Beijing before COVID-19, while only 16% have returned back; all commuters decreased their commuting times during COVID-19, while only 75% have reverted to normal. The findings reveal variations in human activities caused by COVID-19 that can support targeted urban management in the post-epidemic era.

### 1. Introduction

The COVID-19 pandemic, along with its various intervention measures, have brought significant changes in human life. Among them, the changes in human daily activities (e.g., dwelling, working, shopping, and recreation) are the most essential because they are closely related to major aspects of human life such as commerce (Donthu & Gustafsson, 2020), transportation (Huang et al., 2020), employment (Almeida & Santos, 2020) and environment (Wang & Su, 2020). Therefore, revealing how and to what extent COVID-19 has changed human daily activities can help us understand the influence of the epidemic and thereby support future urban management, in areas such as economic development, traffic operation, employment stability, and environment protection, so as to better improve urban resilience and sustainability (Kakderi, Oikonomaki & Papadaki, 2021; Lai, Webster, Kumari & Sarkar, 2020; Sharifi & Khavarian-Garmsir, 2020). However, existing

studies about this issue mainly focus on changes in general human mobility patterns (e.g., mobility intensity, mobility characteristics, and mobility behaviors among different population groups); few studies have investigated changes in specific human daily activities. The changing patterns of these activities with the progress of COVID-19 and the mechanism behind these changes thus remain unclear and worthy of study.

Regarding changes in general human mobility patterns caused by COVID-19, related research has experienced explosive growth (for a review, see Benita, 2021). It can be divided into four categories. The first category mainly focuses on changes in human mobility intensity. Reduction in both long-distance inter-city travel intensity (Gibbs et al., 2020; Parr, Wolshon, Renne, Murray-Tuite & Kim, 2020) and short-distance intra-city movement intensity (Beria & Lunkar, 2021; Yabe et al., 2020; Zhang et al., 2021) has been observed. The second category mainly focuses on changes in human mobility characteristics.

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Reduction of human activity space (as measured by metrics such as moving distance and radius of gyration) and structural changes in mobility networks (becoming more local and clustered) have been detected (Heiler et al., 2020; Pan et al., 2020; Schlosser et al., 2020). The third category mainly focuses on changes in mobility behaviors among different demographic groups. Results have shown that both mobility intensity and activity space declined considerably more among older people because they are at higher risk from the epidemic and among high-income groups because it is much easier for them to work remotely (Bonaccorsi et al., 2020; Iio, Guo, Rees & Wang, 2021; Pullano, Valdano, Scarpa, Rubrichi & Collizza, 2020; Zhang et al., 2021). The fourth category mainly focuses on the relationship between human mobility changes and COVID-19 transmission. Results have shown that decline in the number of daily new confirmed cases is strongly correlated with reduction in human mobility and that there exists a time lag effect between them (Nouvellet et al., 2021; Carteni, Di Francesco & Martino, 2020; Wang, Pei, Liu, & Song, 2020; Xiong, Hu, Yang, Luo & Zhang, 2020).

In addition to these general mobility patterns, changes in specific human daily activities are also important, in that different types of activities reflect different aspects of human life, but few studies have been conducted due to the lack of appropriate observation data. Some existing studies, which we review in the “Related works” section below, attempted to explore changes in the ratio and intensity of different types of human activities during COVID-19. However, these studies were mainly based on questionnaire surveys or analyzing people’s visits to different types of facilities (e.g., residential areas, workplaces, supermarkets, and parks). Thus on the one hand, results may be biased and cannot reveal overall patterns by movement type, and on the other hand, long-term observation and comparison among different epidemic periods is lacking.

In this paper, taking Beijing as a case study, we attempt to track intensity changes in two basic human daily activities, namely, dwelling and working, over different stages of COVID-19. To achieve this, big data for one-year longitudinal mobile phone positioning, including more than 31 million users, were used to detect human dwelling and working behaviors before, during COVID-19 outbreak, and after COVID-19 was under control, which are expressed as several time series indicators. Then, the time series clustering method was utilized to analyze the patterns of changes in dwelling and working intensity at regional scale and individual scale. The analysis at regional scale can indicate the impact of COVID-19 on the overall pattern of human dwelling and working activities in a city; while the analysis at individual scale can indicate the direct impact of COVID-19 on each individual’s activity behavior. To some extent, the results of the latter can be used to explain the results of the former because a city is a system composed of individuals within it while different individuals may have different responses to the epidemic.

The remainder of this paper is organized as follows. Existing works on analyzing human activity changes caused by COVID-19 are reviewed in Section 2. The study area and data are introduced in Section 3. The methodology used is described in Section 4. Results and discussion of them are presented in Section 5 and 6. Several conclusions are provided in Section 7.

## 2. Related works

Existing studies on changes in human daily activities caused by COVID-19 have mainly focused on the ratio and intensity change of different types of activities. These studies can be divided into two categories according to the data used: 1) studies based on questionnaire survey data; and 2) studies based on human mobility data. For the first category, a variety of questionnaire surveys have been conducted in different regions to directly investigate respondents’ activity patterns before and during COVID-19. For example, based on a sample of about 2500 respondents from the Netherlands Mobility Panel (MPN), de Haas,

Faber and Hamersma (2020) investigated changes in human outdoor activities since the crisis and found that 80% of people reported less activity outside of their home. Based on a panel web-survey conducted in Japan’s Kanto Region, Parady, Taniguchi and Takami (2020) modeled behavioral changes of residents’ non-work-related activities and observed severe reduction in leisure activities and eating out (alone and in groups) and moderate reduction in grocery shopping. Based on a paper-based panel survey conducted in Istanbul, Turkey, Shakibaei, De Jong, Alpkökin and Rashidi (2021) estimated the reduction in home-working, social/recreational/leisure (SRL) and shopping activities during the early stages of the epidemic and revealed the heterogeneity of this reduction among different socio-demographics groups.

For the second category, different types of human mobility data were used to indirectly reflect changes in human activities by analyzing people’s visits to different types of facilities. For example, based on map navigation records, Huang et al. (2020) compared the frequency of human visits to different types of venues and found that the proportion visiting residential areas greatly increased while the proportion visiting transport facilities rapidly declined after the COVID-19 outbreak. Based on county-level cell phone location data, Sehra, George, Wiebe, Fundin and Baker (2020) tracked changes in cell phone activity in different categories of places and found that with growth of COVID-19 cases, such activity reduced in workplace, transit station, and retail locations and increased in residential places. Based on cell phone mobility data from SafeGraph, Inc, Levin, Chao, Wenger and Proctor (2020) measured changes in the ratio of populations stayed at home in California, Georgia, Texas, and Washington during COVID-19 and found that the change patterns correlate with socioeconomic factors, cluster geographically, and reveal sub-populations migrating out of urban areas. Based on data collected from Google’s Community Mobility Reports and the Oxford Coronavirus Government Response Tracker, Geng, Innes, Wu and Wang (2021) analyzed changes in the number of park visitors at global, regional and national levels, and found that park visitation has increased since the outbreak of COVID-19. Similarly, based on pedestrian (walking/hiking/running) and ride (cycling) tracking data, Venter, Barton, Gundersen, Figari and Nowell (2020) estimated changes in recreational use of green space during the COVID-19 outbreak in Oslo, Norway and found that human outdoor recreational activity increased by 291% during lockdown relative to a 3 year average for the same days.

Although these studies have made substantial progress, some problems still exist. First, the information collected through questionnaire survey may be biased because it is usually influenced by the subjective feelings of respondents. Meanwhile, a limited number of samples usually cannot reveal overall activity patterns of all population. Second, even though various mobility data have been applied, the analysis only focused on the changes in the total number of visits or activities in different types of urban places and the heterogeneity of this change in different regions and among different individuals still remains unknown. Third, most studies only compared human activity patterns during COVID-19 with a baseline (before COVID-19 or the same period of the previous year); long-term observation and comparison among different epidemic periods is lacking.

As compared to these studies, our study stands to contribute to the existing international research on such issue in three ways. First, the data we analyze are fine-grained mobile phone positioning big data, which are collected passively with high coverage and thereby have the potential to reveal actual human activity change patterns. Second, besides analyzing the overall intensity changes in human dwelling and working activity, we further explore the pattern of this change in different regions and among different individuals, which can help reveal the impact of COVID-19 on different urban functions and different population groups. Third, a one-year observation is conducted by constructing several time series indicators, which can improve the short-, medium-, and long-term understanding of changes in human activity and thereby help compare changes over different epidemic stages.

### 3. Study area and data

#### 3.1. Study area

The area studied in this research is Beijing, the capital city of China (Fig. 1). During outbreak of COVID-19, Beijing experienced rapid spread of the disease, and the daily life of citizens was greatly affected. As of December 2020, a total of 957 cases, including 759 local cases and 198 cases imported from overseas, were confirmed in Beijing (Beijing Municipal Health Commission, 2020a). The total number of cases in different districts is shown in Fig. 1(a), from which we can see the cases are mainly distributed in the main urban area, inside the 6th ring road. Therefore, our subsequent analysis is mainly focused on the area inside the 6th ring road; the detailed distribution of communities with confirmed COVID-19 cases in this area is shown in Fig. 1(b).

#### 3.2. Mobile phone positioning data

Mobile phone positioning data continuously record the location information of phone users and have been widely used to track human daily activities (e.g., Jiang, Ferreira & González, 2017; Thuillier, Moalic, Lamrous & Caminada, 2017; Wu, Wang, Fan, & Yang, 2020; Zhao, Liu, Yu & Hu, 2020). In this paper, we used longitudinal mobile phone data to conduct long-term observation of human dwelling and working activities and track intensity changes in them over the course of COVID-19.

Based on the changes in the daily number of new cases shown in Fig. 2, we selected 12 months (from September 2019 to August 2020) as our study period. Moreover, we divided it into three stages: before COVID-19, during COVID-19 outbreak, and after COVID-19 was under control (Fig. 2). Considering that human dwelling and working activities are generally repeated on a weekly basis (Schlich & Axhausen, 2003), so that one-week data is sufficiently representative to reflect their general pattern (Huang, Levinson, Wang, Zhou & Wang, 2018), for each month we further selected one week (excluding holidays) as a sample week to reduce the amount of calculation. The limitation of such data sampling is that human activity changes between different weeks in the same month cannot be detected. However, our research mainly focuses on long-term changes, i.e., changes over different stages of COVID-19, therefore small short-term changes during a month can be ignored and they have no

significant impact on our final analysis results. Table 1 shows the dates of all sample weeks. For each sample week, we extracted the mobile phone data for all users and subjected them to further analysis.

The mobile phone positioning data we used were acquired from one of the three communication operators in China; this operator accounts for more than 60% of the mobile phone market in Beijing, meaning that more than 60% of the population are represented in the data. Compared with census statistic data, this dataset may lack representativeness for rural, minor and elder people due to the low penetration rate of mobile phones among them, but this does not influence our study significantly because they only account for a relatively small proportion of the total population and are only related to dwelling activity. Table 1 shows the total number of users during each sample week, from which we can see that the number of users decreased when COVID-19 broke out in January 2020 and then gradually increased. On average, each one-week dataset includes about 17 million users before COVID-19, 14 million users during COVID-19 outbreak, and 16 million users after COVID-19 was under control.

The location information of each user is recorded as shown in Table 2, which contains five fields: user ID, the mobile phone tower that a user was located, the tower's longitude and latitude, and a timestamp. To protect personal privacy, the data have been fully anonymized by encrypting user ID and no individual person can be identified or associated with any external information.

### 4. Methodology

The methodological framework of this study can be roughly divided into three parts. First, the dwelling and working behaviors of each user during each sample week were detected by inferring their home and work locations based on the mobile phone positioning data. Then, changes in human dwelling and working intensity from before to during COVID-19 outbreak and after COVID-19 was under control were tracked from two perspectives: regional scale and individual scale. At regional scale, we divided the city on a spatial grid and counted the number of users dwelling and working inside each grid square as a measurement of regional dwelling and working intensity. At individual scale, we counted the number of days that a user dwells and works in Beijing during a week as a measurement of individual dwelling and working intensity.

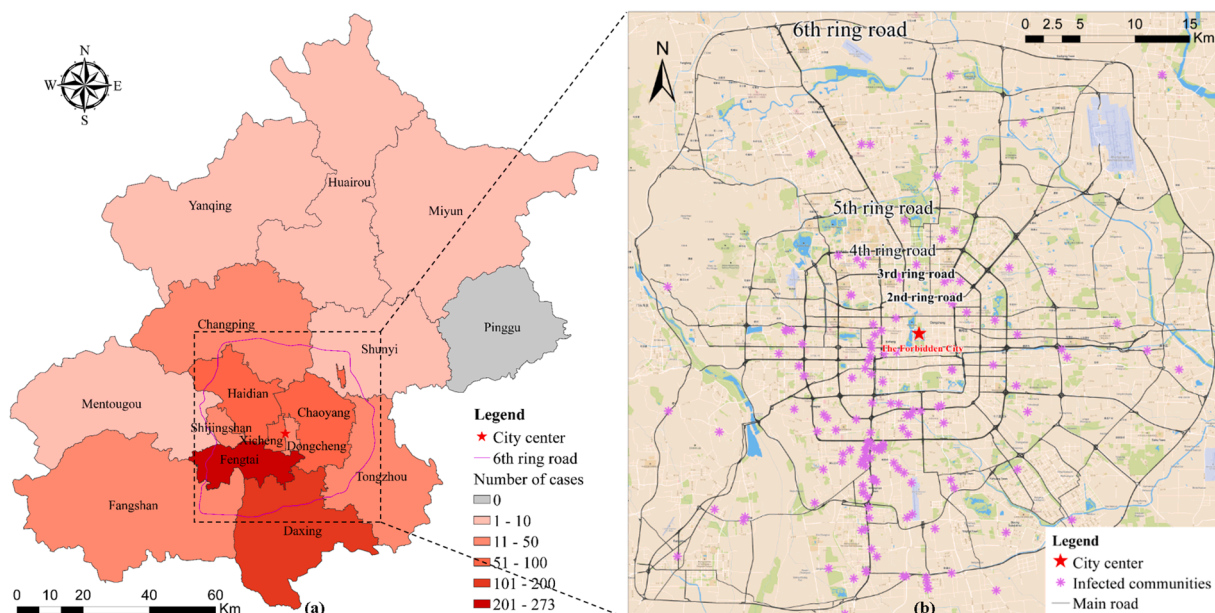


Fig. 1. Study area of Beijing. (a) Spatial distribution of confirmed COVID-19 cases at district scale; (b) Spatial distribution of communities with confirmed COVID-19 cases inside 6th ring road.

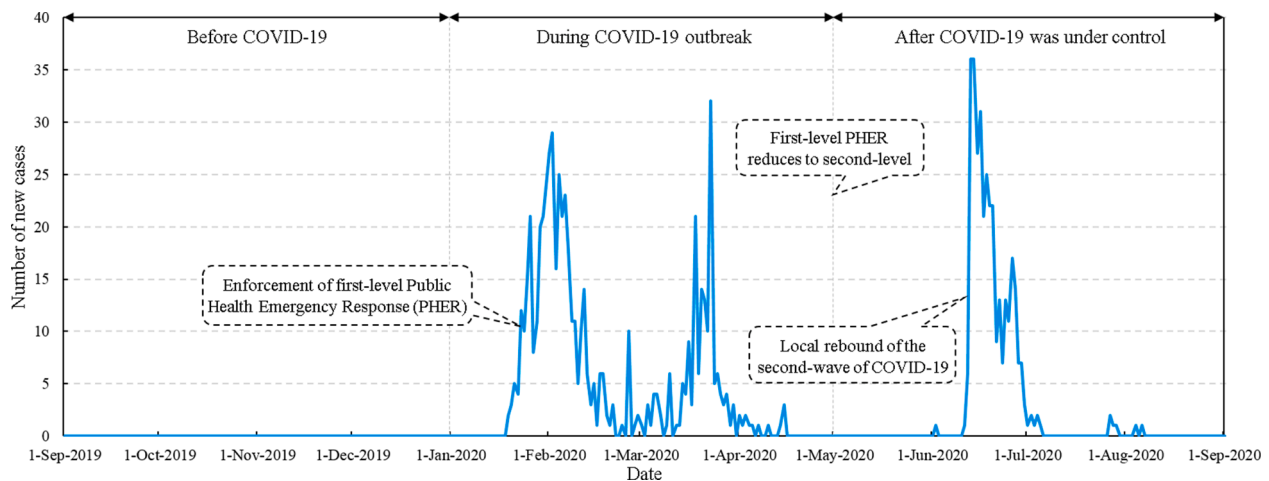


Fig. 2. Time division of the study period according to the daily number of new cases (Data source: Beijing Municipal Health Commission at <http://wjw.beijing.gov.cn/wjwh/ztlzxxgzbd/>).

**Table 1**  
Sample weeks and total number of users in each week.

Month	Date	Number of Users (million)	Month	Date	Number of Users (million)
September 2019	16–22	16.62	March 2020	16–22	13.81
October 2019	21–27	17.15	April 2020	13–19	14.81
November 2019	18–24	17.36	May 2020	18–24	15.91
December 2019	16–22	17.39	June 2020	15–21	15.94
January 2020	13–19	16.46	July 2020	20–26	15.98
February 2020	17–23	12.71	August 2020	17–23	16.55
	February			August	

**Table 2**  
Example of a user’s mobile phone positioning data.

User ID	Tower ID	Longitude	Latitude	Timestamp
04d678***98bf92	24,367	116.3***7	39.8***3	2020-03-16 00:00:11
04d678***98bf92	12,746	116.6***4	39.9***8	2020-03-16 00:00:23
...	...	...	...	...
04d678***98bf92	12,937	116.6***9	39.9***4	2020-03-16 23:59:37
04d678***98bf92	20,689	116.3***6	39.5***7	2020-03-16 23:59:56

4.1. Detecting human dwelling and working behavior

Based on users’ movement information recorded in mobile phone positioning data, we can identify the home and work locations of each user; for each user, their visits to these locations indicate their dwelling and working behavior, respectively. Therefore, for each sample week, we defined 6 variables to reflect the dwelling and working behavior of users (Table 3). The first variable, *ActiveDays*, is the number of days a

**Table 3**  
Variables reflecting human dwelling and working behavior over a week.

Variables	Description	Range
ActiveDays	Number of days a user is active during a week	1 to 7
HomeLocation	Detected home location of a user	-
HomeDays	Number of days a user dwells at detected home location	0 to 7
WorkLocation	Detected work location of a user	-
WorkDays	Number of days a user works at detected work location	0 to 5
HWDistance	Distance between home location and work location	-

user is active, which reflects how many days the user dwells in Beijing during a week. Here, an active day means that a user appears in Beijing for at least 3 h during the dwelling period (22:00–06:00) and 3 h during the working period (between 09:00–12:00 and 14:00–17:00) in a day. The second variable, *HomeLocation*, is the detected home location of a user in a week. First, for each day, we identified the location that a user most frequently visited during the dwelling period as a candidate home location. Then, for the whole week, we counted the number of days on which each candidate’s home location appeared and selected the most frequent location as the final home location. The number of days that the detected home location appeared in a week is recorded as the third variable, *HomeDays*, and it reflects the number of days that a user dwells at this location. The fourth variable (*WorkLocation*) and the fifth variable (*WorkDays*) are the detected work location of a user and the number of days they work at this location during a week. The detection method is the same as that for home location detection described above, while the timeframe is set to the working period on weekdays. The last variable, *HWDistance*, is the distance between detected home location and work location.

Based on these variables, we can classify the users into two groups and three classes, respectively (Table 4). According to *ActiveDays*, the users were divided into the “usual residents” who dwelled in Beijing all week and “travelers” between Beijing and other cities, who dwelled in Beijing for less than 7 days per week. According to *HomeDays*, *WorkDays* and *HWDistance*, the users were divided into three classes. If *HomeDays* ≥ 4 and *WorkDays* ≥ 3, the users were considered to have fixed dwelling and working places. If *HomeDays* < 4 or *WorkDays* < 3, the users were considered to be without fixed dwelling or working place. Users with fixed dwelling and working places were further split according to *HWDistance*. If *HWDistance* ≥ 1 km, the users were considered to commute between dwelling and working places; if *HWDistance* < 1 km,

**Table 4**  
User classification based on dwelling and working behavior.

Type	Name	Classification rules
Group 1	Usual residents	ActiveDays=7
Group 2	Travelers between Beijing and other cities	ActiveDays<7
Class 1	Users commuting between dwelling and working places	HomeDays ≥ 4 and WorkDays ≥ 3 and HWDistance ≥ 1km
Class 2	Users staying at home or working near home	HomeDays ≥ 4 and WorkDays ≥ 3 and HWDistance < 1km
Class 3	Users without fixed dwelling or working places	HomeDays < 4 or WorkDays < 3

the users were considered to stay at home or work near home. The number of different types of users during different sample weeks will be analyzed later, and changes caused by the COVID-19 pandemic will be discussed.

4.2. Tracking human dwelling and working intensity at regional scale

Changes in human dwelling and working intensity may differ from region to region due to differences in urban functions between regions. To track this difference, we divided the city into 500 m by 500 m grid squares and calculated the dwelling and working intensity of each square during different sample weeks. Here, the dwelling and working intensity of a square are defined as the total number of phone users who dwell or work in the square respectively. For each square, two time series were constructed to indicate the process of change in dwelling and working intensity over 12 sample weeks, which can be expressed as:

$$S_i(Dwell) = [I_1(Dwell), I_2(Dwell), I_n(Dwell), \dots, I_{12}(Dwell)] \tag{1}$$

$$S_i(Work) = [I_1(Work), I_2(Work), I_n(Work), \dots, I_{12}(Work)] \tag{2}$$

where  $S_i(Dwell)$  and  $S_i(Work)$  are the time series of dwelling and working intensity in the  $i$  th grid square, and  $I_n(Dwell)$  and  $I_n(Work)$  are the dwelling and working intensity during the  $n$  th sample week. Meanwhile, to compare changes in dwelling and working intensity between different squares, we adopted the sum normalization method for each time series to eliminate the effect of magnitude. The normalization was calculated as:

$$\text{Normalized\_}S_i = \left[ \frac{I_1}{\sum_{n=1}^{12} I_n}, \frac{I_2}{\sum_{n=1}^{12} I_n}, \frac{I_n}{\sum_{n=1}^{12} I_n}, \dots, \frac{I_{12}}{\sum_{n=1}^{12} I_n} \right] \tag{3}$$

Then, a k-means clustering algorithm was applied to group squares with similar change patterns of dwelling and working intensity into the same class. The similarity between any two time series was measured based on their correlation distance, which was calculated as:

$$d(S_i, S_j) = 1 - \frac{\sum (S_i - \bar{S}_i)(S_j - \bar{S}_j)}{\sqrt{\sum (S_i - \bar{S}_i)^2 \sum (S_j - \bar{S}_j)^2}} \tag{4}$$

where  $S_i$  and  $S_j$  represent two normalized time series of different squares. The number of clusters was determined by the Elbow method (Bholowalia & Kumar, 2014).

Furthermore, to correlate urban functions with changes in dwelling and working intensity, we used POI (Point of Interest) data to obtain the function semantics of the clusters. The POIs were categorized into 13 types as shown in Table 5. The number of different types of POIs in a grid square can provide indications of urban functions. However, from the table, we can see that the total numbers of POIs of different types are uneven, which may impact the inference of urban functions. To reduce such impacts, the term frequency-inverse document frequency (TF-IDF) method (Cai, Xu, Liu, & Ma, 2019; Yuan, Zheng & Xie, 2012) was

**Table 5**  
POI categories and their statistical information.

POI type	Count	POI type	Count
Retailing & Shopping	48,481	Finance and Insurance	11,747
Enterprises	43,575	Medical Services	10,592
Food & Beverage	42,801	Sports and Entertainment	7,728
Daily Life Services	30,373	Accommodation Services	7,060
Science, Culture, and Education	21,844	Tourist Attraction	4,154
Residential Building	18,052	Transportation Services	3,116
Governmental and Social Organization	11,825		

applied. First, for each grid square, the TF-IDF value of each POI type was calculated as:

$$T_{ij} = \log\left(\frac{n_{ij}}{n_i}\right) \times \log\left(\frac{N}{N_j + 1}\right) \tag{5}$$

where  $T_{ij}$  is the TF-IDF value of the  $j$  th POI type in the  $i$  th grid square;  $n_{ij}$  is the number of  $j$  th type of POIs in the  $i$  th square;  $n_i$  is the total number of all types of POIs in the  $i$  th square;  $N$  is the total number of squares in the city; and  $N_j$  is the number of squares that contains the  $j$  th type of POIs. Then, for each POI type, the mean value of TF-IDF of the squares belonging to the same cluster were calculated. A higher value means that this type of POI is not only rich in this cluster but also poor in other clusters, which indicates that this POI type (urban function) is representative in this cluster.

4.3. Tracking human dwelling and working intensity at individual scale

Different individuals may have different responses to the epidemic due to their different demographics. Therefore, in this section, we tracked changes in each mobile phone user’s dwelling and working intensity. First, the variable *ActiveDays*, extracted in Section 3.1, was used to reflect the number of days that a user dwelled in Beijing during each sample week. For each user, change in *ActiveDays* over 12 sample weeks can form a time series:

$$S_i(ActiveDays) = [ActiveDays_1, ActiveDays_2, ActiveDays_n, \dots, ActiveDays_{12}] \tag{6}$$

where  $S_i(ActiveDays)$  is the time series of the  $i$  th user and  $ActiveDays_n$  is the number of days that the  $i$  th user dwelled in Beijing during the  $n$  th sample week. Based on this time series, a k-means clustering algorithm was applied to classify users into different groups, such as local residents who are always in Beijing (e.g.:  $S(ActiveDays) = [7, 7, 7, 7, 7, 7, 7, 7, 7, 7, 7, 7]$ ); travelers with short stays in Beijing (e.g.:  $S(ActiveDays) = [0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]$ ); migrant residents who left Beijing before COVID-19 and have not come back yet (e.g.:  $S(ActiveDays) = [7, 7, 7, 7, 0, 0, 0, 0, 0, 0, 0, 0]$ ); newcomers, who came to Beijing after the outbreak of COVID (e.g.:  $S(ActiveDays) = [0, 0, 0, 0, 0, 0, 0, 7, 7, 7, 7, 7]$ ), and others.

For the local residents, we further constructed a time series of their *WorkDays* over 12 sample weeks to reflect changes in their working intensity, which can be expressed as:

$$S_i(WorkDays) = [WorkDays_1, WorkDays_2, WorkDays_n, \dots, WorkDays_{12}] \tag{7}$$

where  $S_i(WorkDays)$  is the time series of  $i$  th resident and  $WorkDays_n$  is the number of days that the  $i$  th resident commuted to work during the  $n$  th sample week. Based on this time series, a k-means clustering algorithm was applied to classify these local residents into different groups, such as home stayers who stayed at home all the time (e.g.:  $S(WorkDays) = [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]$ ), commuters who decreased their commuting times during COVID-19 and recovered to normal after COVID-19 was under control (e.g.:  $S(WorkDays) = [5, 5, 5, 5, 0, 0, 2, 3, 4, 5, 5]$ ), commuters who stopped commuting and have not returned to work after COVID-19 was under control (e.g.:  $S(WorkDays) = [5, 5, 5, 5, 0, 0, 0, 0, 0, 0, 0, 0]$ ), and others.

5. Results

5.1. Basic statistics for human dwelling and working behavior

As discussed in Section 3.1, six variables were extracted in each sample week to reflect the dwelling and working behavior of a user. According to these variables, the users were divided into two groups and three classes. The temporal changes in the numbers of each group of users are shown in Fig. 3, and changes in the number of users in each

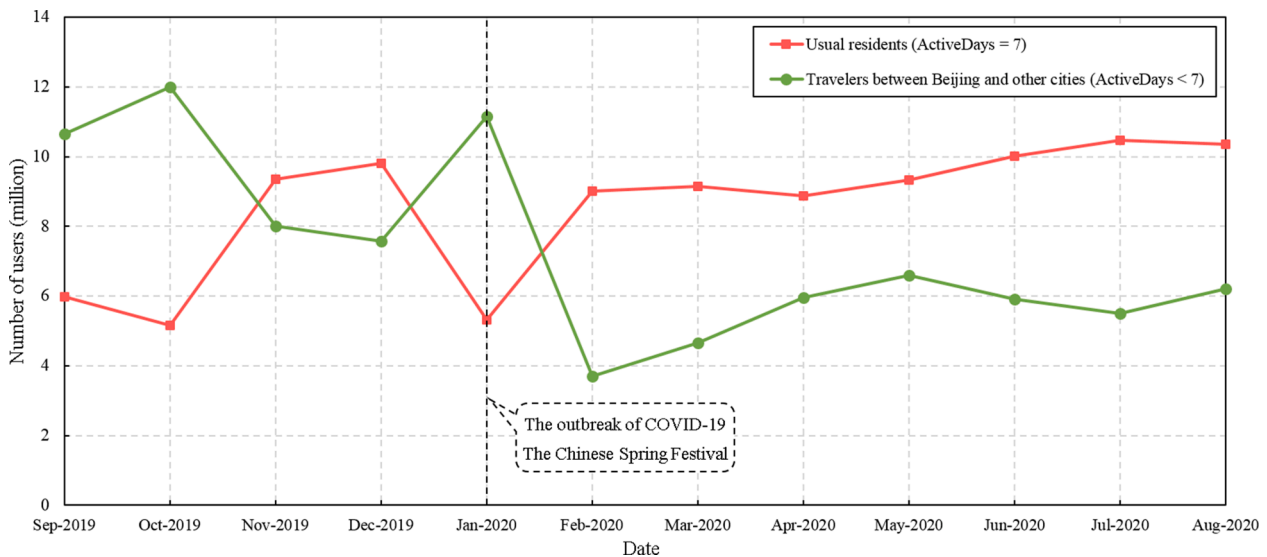


Fig. 3. Temporal changes in the numbers of each group of users classified by their number of active days during each sample week.

class are shown in Fig. 4.

During September and October 2019, high demand for business and recreational trips caused strong intensity of inter-city mobility, so the number of travelers was larger than that of usual residents. Similarly, the number of users without fixed dwelling or working places was larger than that of users with fixed dwelling and working places. As the end of the year came, this type of travel intensity decreased, so that the number of usual residents (mainly composed of users with fixed dwelling and working places) increased, while the number of travelers (mainly composed of users without fixed dwelling or working places) decreased.

However, as COVID-19 broke out and the Chinese Spring Festival (Chinese New Year) came in January 2020, people started to return home and inter-city travel intensity increased again, which resulted in rapid decrease in the number of usual residents and increase in the number of travelers. Similarly, the number of users with fixed dwelling and working places decreased while the number of users without fixed dwelling or working places increased. To prevent and control the epidemic, a series of travel restriction measures were quickly implemented; therefore, in February 2020, the number of usual residents increased while the number of travelers reached its lowest point.

Meanwhile, the closure of schools and other departments made the number of users commuting between dwelling and working places reach its lowest point, while the number of users staying at home or working near home reached its highest. Subsequently, as the epidemic gradually came under control, the number of commuters and travelers gradually increased and the number of users staying at home or working near home gradually decreased.

### 5.2. Changes in human dwelling and working intensity at regional scale

In this section, the changes in human dwelling and working intensity at regional scale are presented. First, three sample weeks (represented as 201910, 202002 and 202006 in October 2019, February 2020, and June 2020 respectively), were selected to visualize the spatial distribution (Fig. 5) and spatial change (Fig. 6) in human dwelling and working intensity relative to the three stages of the epidemic (before, during and once it was under control). From the figures, we can see that the spatial distribution of working intensity is more clustered than that of dwelling intensity and its changes over different stages of COVID-19 are also larger. During COVID-19 outbreak, dwelling intensity increased in some

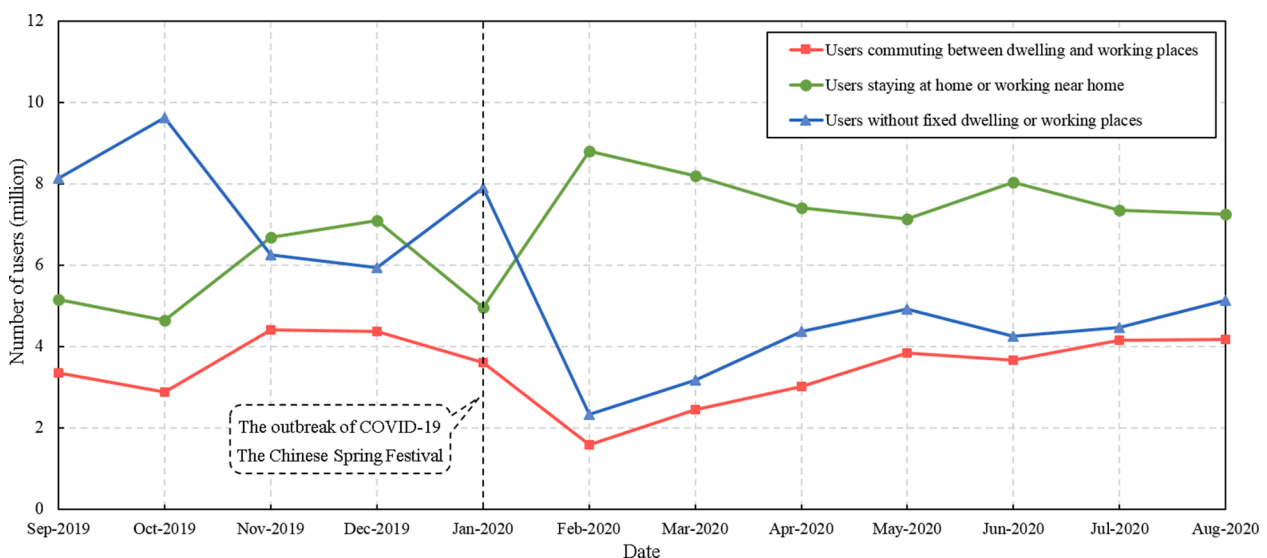


Fig. 4. Temporal changes in the numbers of each class of users classified by their commuting behaviors during each sample week.

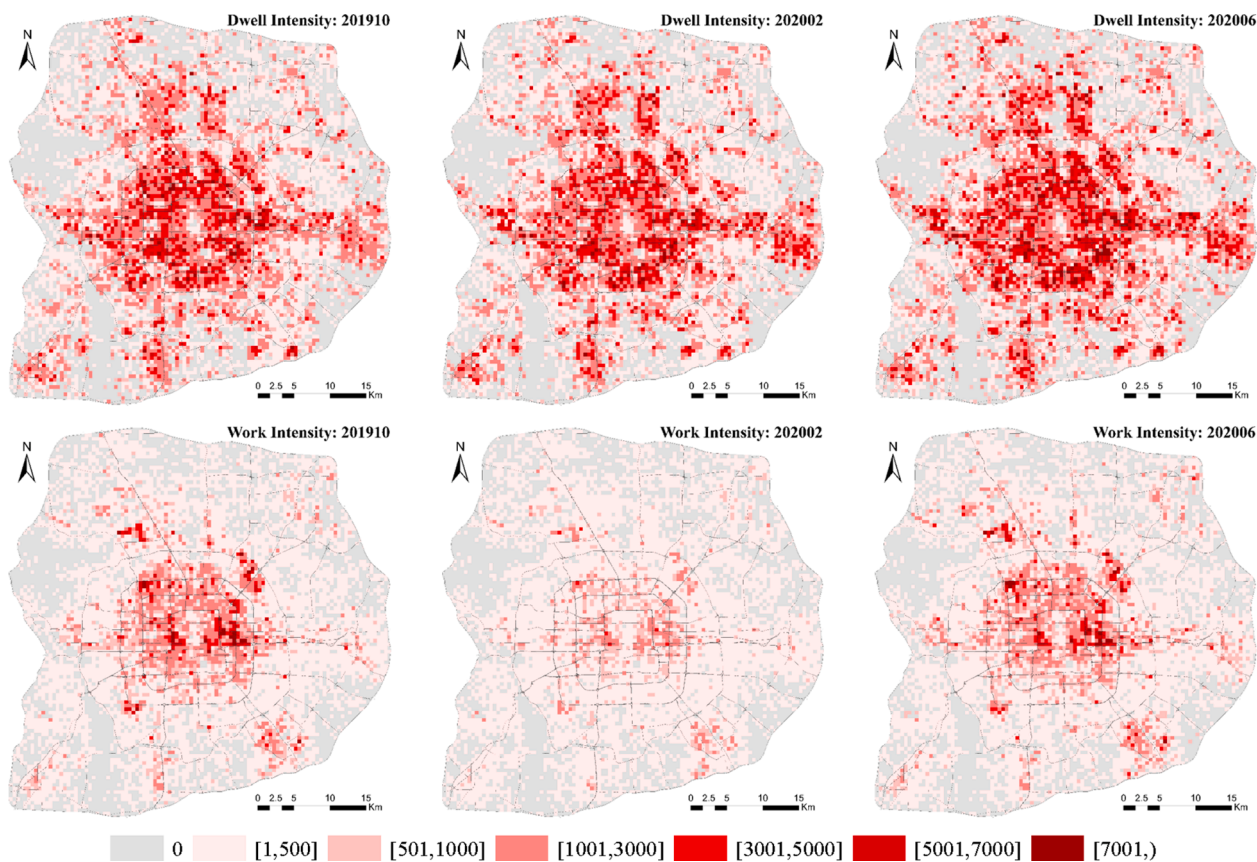


Fig. 5. Spatial distribution of human dwelling and working intensity in Beijing before, during COVID-19 outbreak, and after COVID-19 was under control.

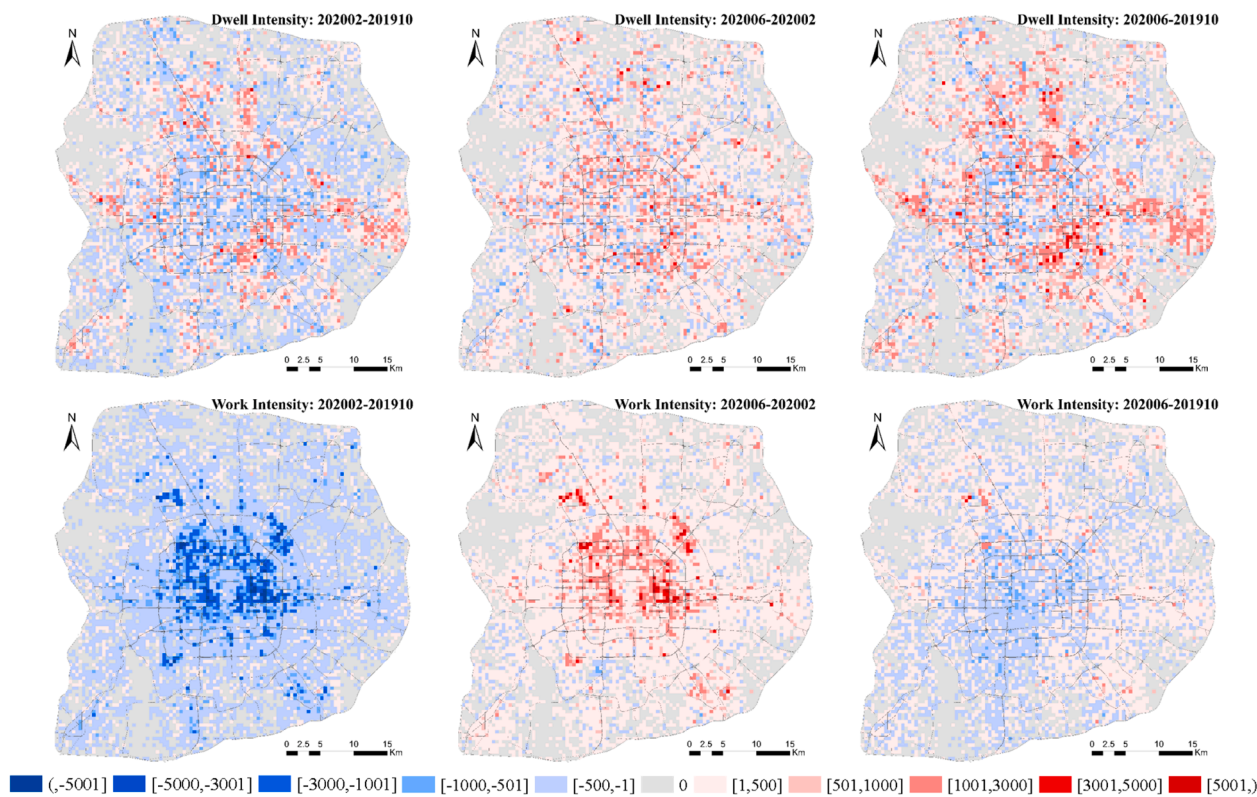


Fig. 6. Spatial changes in human dwelling and working intensity in Beijing before, during COVID-19 outbreak, and after COVID-19 was under control.



grid squares and decreased in others while working intensity decreased in all squares. After COVID-19 was under control, both dwelling and working intensity increased in most squares. Compared to the situation before COVID-19, dwelling and working intensity in some squares has recovered or even become stronger, although that in some squares has not recovered.

Next, to further explore the detailed change process for human dwelling and working intensity, the time series clustering method was applied to group grid squares with similar changing patterns into a cluster, and the TF-IDF method was applied to explore its relationship with urban function.

Based on the time series of dwelling intensity, the squares were grouped into four clusters. Fig. 7 shows the spatial distribution and the center of each cluster. Table 6 gives the TF-IDF values of all the POI types in each cluster and the corresponding internal and external ranks. We can see that the temporal changes in human dwelling intensity before COVID-19 showed a similar pattern for all clusters. However, as COVID-19 broke out and the Chinese Spring Festival came in January 2020, it showed distinct characteristics in different classes.

In cluster C1, human dwelling intensity remained basically unchanged, and the grid squares were mainly distributed in big residential areas such as Tiantongyuan Community and Tongzhou District (sub-center of Beijing). Correspondingly, the TF-IDF values of Residential Building, Daily Life Services, and Sports and Entertainment are the largest among all clusters.

In cluster C2, human dwelling intensity increased gradually and became stronger than that before COVID-19. The squares were mainly distributed in suburbs like Shijingshan District and the dominant POI types were Residential Building, Retailing & Shopping, Daily Life Services, Governmental and Social Organization, and Tourist Attraction.

In cluster C3, human dwelling intensity decreased about 40% during COVID-19 outbreak and then gradually recovered to the same level as before COVID-19. The squares were mainly distributed in certain work-related areas such as Wangfujing Commercial Street and Chaopi Logistics Center, where the dominant POI types are Retailing & Shopping, Enterprises, Governmental and Social Organization, Medical Services, Accommodation Services, and Transportation Services.

In cluster C4, human dwelling intensity also decreased about 40%; however, it has not recovered as of August 2020. The squares were mainly distributed in areas with a concentration of universities like

Wudaokou and Zhongguancun Street. Correspondingly, the main POI types are Science, Culture, and Education; Food & Beverage; and Finance and Insurance. Note that the Xinfadi Wholesale Market, where the second wave of COVID-19 in Beijing initially broke out, also belongs to this cluster.

Based on the time series of working intensity, the grid squares were also grouped into four clusters (Fig. 8). The TF-IDF values of all the POI types in each cluster are shown in Table 7. We can see that for all clusters, the temporal changes in human working intensity show an upward trend before COVID-19, but as COVID-19 broke out and the Chinese Spring Festival came in January 2020, working intensity decreased about 60% in the whole city and reached its lowest value in February 2020. After that, the changes showed different patterns across clusters.

In cluster C1, human working intensity recovered gradually and has reached the level it was at before COVID-19. The regions covered by this cluster are mostly business-related areas such as Zhongguancun Street (the largest electronic market), Wangjing Business District, and the Central Business District (CBD). The main POI types are Food & Beverage, Retailing & Shopping, Daily Life Services, Medical Services, and Finance and Insurance.

In cluster C2, human working intensity recovered slowly and has only reached half of its level before COVID-19. The covered regions are mainly schools, hotels, and entertainment venues such as Beihai Park and Qianmen Street. Correspondingly, the dominant POI types are Science, Culture, and Education; Sports and Entertainment; and Accommodation Services.

In cluster C3, human working intensity recovered relatively fast and has become stronger than before COVID-19. The covered regions are mainly work-related areas in suburbs, such as Shougang Industrial Park and Yizhuang Economic and Technological Development Zone. The dominant POI types are Enterprises, Residential Building, and Transportation Services.

In cluster C4, human working intensity increased before May 2020 and then began to decrease again after the second wave of COVID-19, in June. The grid squares are mainly distributed in suburbs, and the dominant POI type is Governmental and Social Organization, followed by Tourist Attraction. The Xinfadi Wholesale Market, where the second wave of COVID-19 initially broke out, also belongs to this cluster.

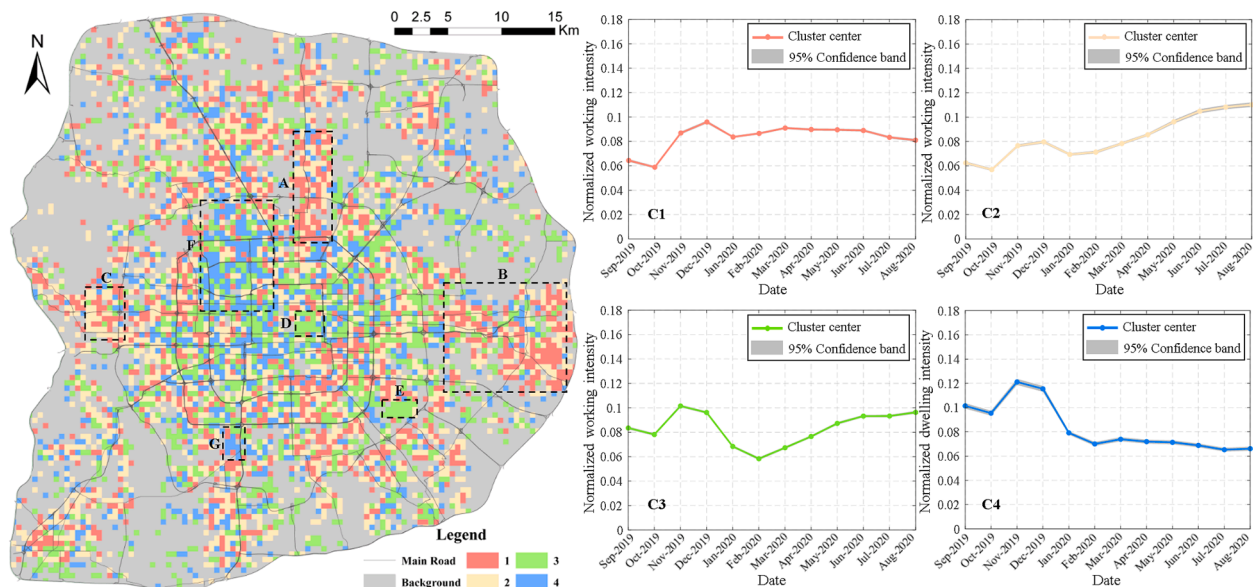
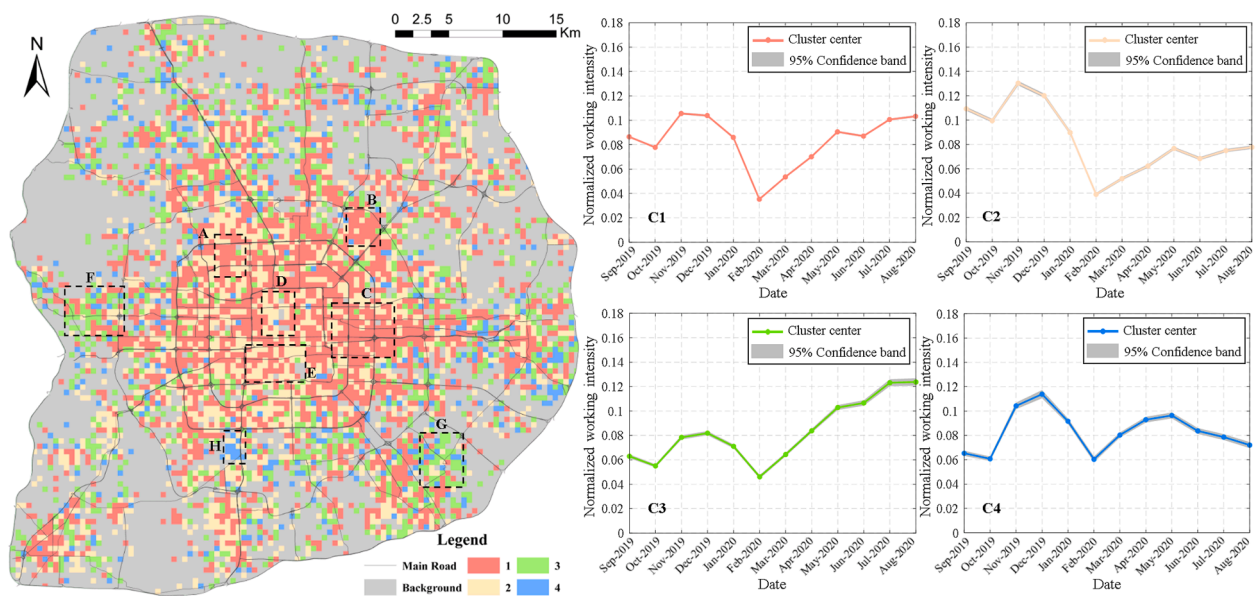


Fig. 7. Clustering result of grid squares according to their temporal changes in human dwelling intensity (A. Tiantongyuan Community; B. Tongzhou District; C. Shijingshan District; D. Wangfujing Commercial Street; E. Chaopi Logistics Center; F. Wudaokou and Zhongguancun Street; G. Xinfadi Wholesale Market).

**Table 6**  
TF-IDF values of the POI types in each cluster (clustered by human dwelling intensity).

POI Type	C1		C2		C3		C4	
	TF-IDF	IR	TF-IDF	IR	TF-IDF	IR	TF-IDF	IR
Retailing & Shopping	0.1139	4	0.1177	4	0.1497	2	0.1135	4
Enterprises	0.1439	2	0.1761	1	0.2071	1	0.1797	1
Food & Beverage	0.1317	3	0.1276	3	0.1434	3	0.1499	3
Daily Life Services	0.1084	5	0.0868	6	0.0684	6	0.0747	6
Science, Culture, and Education	0.1038	6	0.1035	5	0.1007	4	0.1517	2
Residential Building	0.1915	1	0.1671	2	0.0815	5	0.0974	5
Governmental and Social Organization	0.0492	7	0.0508	7	0.0567	7	0.0475	7
Finance and Insurance	0.0273	12	0.0272	11	0.0249	12	0.0303	11
Medical Services	0.0339	8	0.0370	10	0.0389	9	0.0376	10
Sports and Entertainment	0.0283	11	0.0240	12	0.0282	11	0.0277	12
Accommodation Services	0.0166	13	0.0169	13	0.0233	13	0.0225	13
Tourist Attraction	0.0307	10	0.0395	8	0.0312	10	0.0396	8
Transportation Services	0.0331	9	0.0374	9	0.0431	8	0.0378	9



**Fig. 8.** Clustering result of grid squares according to their temporal changes in human working intensity (A. Zhongguancun Street; B. Wangjing Business District; C. Central Business District; D. Beihai Park; E. Qianmen Street; F. Shougang Industrial Park; G. Yizhuang Economic and Technological Development Zone; H. Xinfadi Wholesale Market).

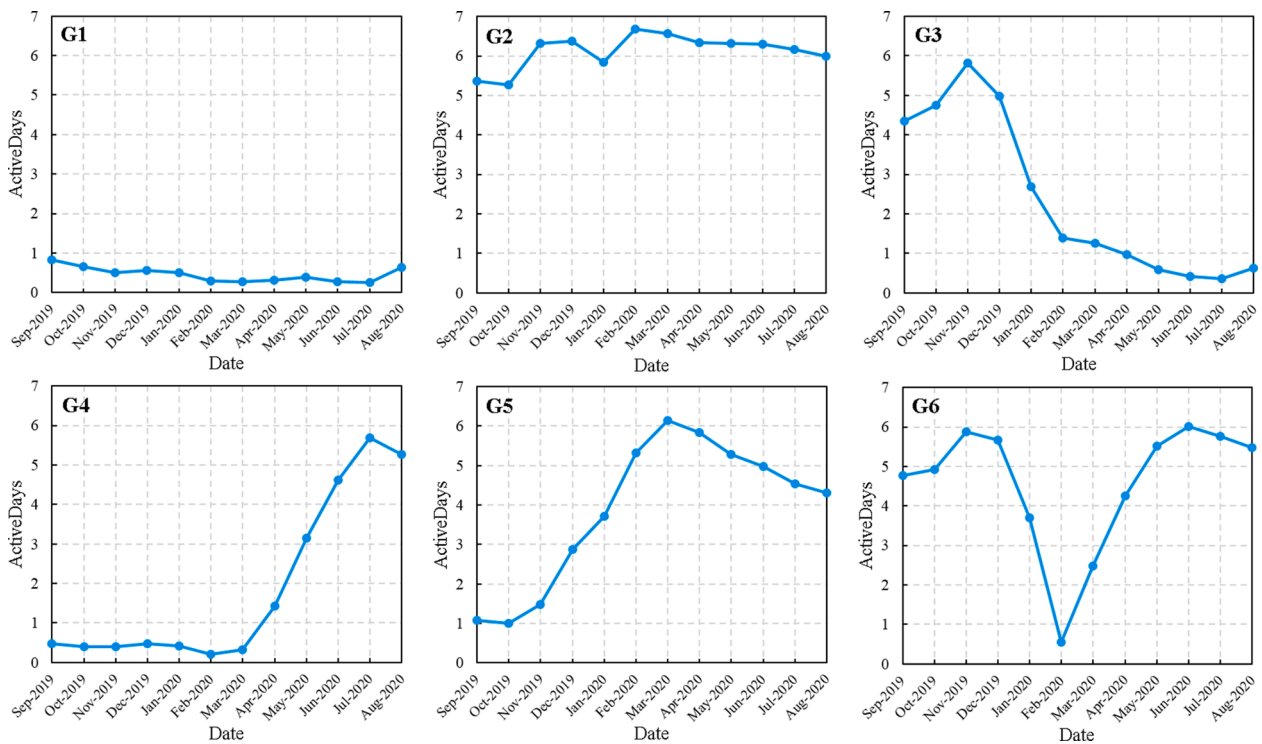
5.3. Changes in human dwelling and working intensity at individual scale

In this section, we track the changes in human dwelling and working intensity at individual scale by applying the clustering method to the time series of *ActiveDays* and *WorkDays* over 12 sample weeks for each

user. In accordance with the time series of *ActiveDays*, the users were clustered into six groups, as shown in Fig. 9. Group G1 shows the low value of *ActiveDays* in all sample weeks, representing travelers who made only a short stay in Beijing. Group G2 shows a high value for *ActiveDays* in all sample weeks, and represents local residents who are

**Table 7**  
TF-IDF values of the POI types in each cluster (clustered by human working intensity).

POI Type	C1		C2		C3		C4	
	TF-IDF	IR	TF-IDF	IR	TF-IDF	IR	TF-IDF	IR
Retailing & Shopping	0.1253	3	0.1195	5	0.1113	3	0.1114	3
Enterprises	0.2004	1	0.1519	2	0.2476	1	0.2287	1
Food & Beverage	0.1502	2	0.1410	3	0.1070	4	0.1018	4
Daily Life Services	0.0886	6	0.0801	6	0.0711	6	0.0802	6
Science, Culture, and Education	0.0979	5	0.1582	1	0.0902	5	0.1014	5
Residential Building	0.1125	4	0.1224	4	0.1513	2	0.1509	2
Governmental and Social Organization	0.0482	7	0.0505	7	0.0463	8	0.0517	7
Finance and Insurance	0.0307	11	0.0264	12	0.0234	11	0.0202	13
Medical Services	0.0389	8	0.0377	9	0.0278	10	0.0247	10
Sports and Entertainment	0.0281	12	0.0305	11	0.0232	12	0.0245	11
Accommodation Services	0.0192	13	0.0211	13	0.0165	13	0.0207	12
Tourist Attraction	0.0309	10	0.0435	8	0.0447	9	0.0501	8
Transportation Services	0.0348	9	0.0367	10	0.0604	7	0.0480	9



**Fig. 9.** Clustering results of users according to their time series of ActiveDays.

always or almost always in Beijing. The value of *ActiveDays* in group G3 was high before COVID-19 but then decreased to near zero, representing migrant residents who left Beijing before COVID-19 and have not come back yet. Group G4 is the opposite of group G3, representing newcomers, who came to Beijing after COVID-19. The value of *ActiveDays* in group G5 increased before COVID-19 and then decreased; it represents visitors who came to Beijing before COVID-19 and left when COVID-19 was under control. The value of *ActiveDays* in group G6 first decreases and then increases; it represents migrant residents who left Beijing before COVID-19 and came back when COVID-19 was under control. The number of users in each group is shown in Table 8, from which we can see that about 37% of users (G1) were travelers who made a short stay in Beijing and about 46% of users (G2, G3 and G6) were residents who dwelled in Beijing before COVID-19. Among these residents, about 43% of them (G3 and G6) were migrant residents who left Beijing before COVID-19 and only 16% (G6) have returned back after COVID-19 was under control.

Local residents in Beijing (group G2 in Fig. 9) were further clustered into five groups according to their time series of *WorkDays* (as shown in Fig. 10). The value of *WorkDays* in group G1 was near zero in all sample weeks, representing home stayers who stayed at home or worked near home the whole time. Groups G2 and G3 showed similar patterns to each other, with the value of *WorkDays* decreasing first and then increasing; they thus represent commuters who decreased commuting times during COVID-19 and then reverted after COVID-19 was under control. The value of *WorkDays* in group G4 decreased near zero during COVID-19 and has not recovered; it represents commuters who stopped commuting and have not returned back to work after COVID-19 was under control. Group G5 is the opposite of group G4, representing residents who started commuting after COVID-19. The number of users in each group is shown in Table 9, from which we can see that about 66% of local residents (G1) stayed at home or worked near home for all time and about 29% (G2, G3 and G4) were commuters commuted between home and work locations. All of these commuters decreased commuting times during COVID-19, while only 75% (G2 and G3) have reverted to normal after COVID-19 was under control.

## 6. Discussion

In the results section, we observed that both human dwelling and working intensity at regional scale and at individual scale have changed significantly over the stages of COVID-19; meanwhile, the changes showed different patterns in different regions and among different individuals. In this section, we will explore the mechanism behind these changes and differences by discussing the factors that may have influenced human dwelling and working intensity during each stage of the epidemic and then provide some implications of our findings for future urban management.

### 6.1. Factors influencing human dwelling and working intensity

Before COVID-19, changes in human dwelling and working intensity were mainly influenced by the coming of the Chinese Spring Festival. At the beginning of this stage, the intensity of human inter-city mobility was strong due to high demand for business and recreational trips. Therefore, travelers with a short stay in Beijing account for the highest proportion among all users (Fig. 3), and both human dwelling and working intensity in the city were relatively low (Fig. 7 and Fig. 8). As

**Table 8**  
Number of users in different groups clustered by their time series of *ActiveDays*.

Groups	G1	G2	G3	G4	G5	G6	Total
Number of users (million)	11.70	8.40	3.85	2.70	2.50	2.38	31.53
Ratio (%)	37.10	26.66	12.21	8.58	7.92	7.53	100

the end of the year came, this type of travel intensity decreased, so that human dwelling and working intensity showed an upward trend; however, from December 2019 to January 2020, the coming of the Chinese Spring Festival boosted human inter-city mobility again. Some people who worked or studied in Beijing but whose hometowns were in other cities started to leave (users belonging to groups G3 and G6 in Fig. 9) while some people who worked or studied in other cities but whose hometown was Beijing started to come back (users belonging to group G5 in Fig. 9). Therefore, dwelling and working intensity in the city decreased again, because the number of people who left was larger than that who returned.

During COVID-19 outbreak, changes in human dwelling and working intensity were mainly influenced by epidemic prevention and control measures. COVID-19 is mainly transmitted via close contact among people, which is strongly associated with human movement (Bi et al., 2020; Rothan & Byrareddy, 2020). Therefore, the key to effectively addressing COVID-19 is restriction of human mobility, which usually includes two aspects: travel restriction measures, such as closure of airports, train stations, and bus stations, which restricts human inter-city mobility (Tian et al., 2020), and stay-at-home policies, such as banning public gatherings, closing schools and businesses, and promoting remote working, which restricts human intra-city mobility (Beijing Municipal Health Commission, 2020b). The former meant that migrant residents who left Beijing before COVID-19 could not come back (users belonging to group G3 and G6 in Fig. 9), while visitors who came to Beijing before COVID-19 could not leave (users belonging to group G5 in Fig. 9). The latter meant that commuters in Beijing had to reduce their commuting times and stay at home (users belonging to groups G2, G3, and G4 in Fig. 10). Therefore, dwelling intensity increased in some residential and suburb areas but decreased in some commercial and education-related areas (Fig. 7), while working intensity decreased rapidly in all regions and reached its lowest value in February 2020 (Fig. 8).

After COVID-19 was under control, changes in human dwelling and working intensity were mainly influenced by the resumption of work and the local rebound of the second wave of epidemic. In this stage, travel restriction measures were gradually canceled, so that people in other cities started coming into Beijing (users belonging to groups G4 and G6 in Fig. 9) and people in Beijing started commuting to work (users belonging to groups G2, G3, and G5 in Fig. 10). As a result, dwelling and working intensity in the city recovered, but to different degrees in different regions. As to dwelling intensity, it has recovered to the same level as before COVID-19 in most regions; however in education-related areas, it has maintained a low value, because schools have not reopened yet, so that students cannot return to the campus (Fig. 7). As to working intensity, it has recovered to the level before COVID-19 in most business-related regions and become even stronger than before COVID-19 in some work-related areas in suburbs. However, in some schools, hotels, entertainment venues, and tourist attractions, it only recovered to half of the level before COVID-19 and sometimes even decreased again when the second wave of the epidemic appeared (Fig. 8).

In summary, the overlap of the Chinese Spring Festival and the COVID-19 epidemic made a direct influence on each individual's movement behavior, changing their dwelling and working intensity. Different combinations of individuals with different dwelling and working intensity changes yielded changes in dwelling and working intensity that varied among regions with different urban functions. To show this mechanism more clearly, the corresponding relationship between the change patterns of human dwelling and working intensity at individual scale and at regional scale are presented in Table 10 and Table 11, respectively.

### 6.2. Implications for future urban management

Different from existing studies that only focus on the overall change pattern of human dwelling and working intensity in a city (Beria & Lunkar, 2021; Huang et al., 2020; Levin et al., 2020; Sehra et al., 2020),

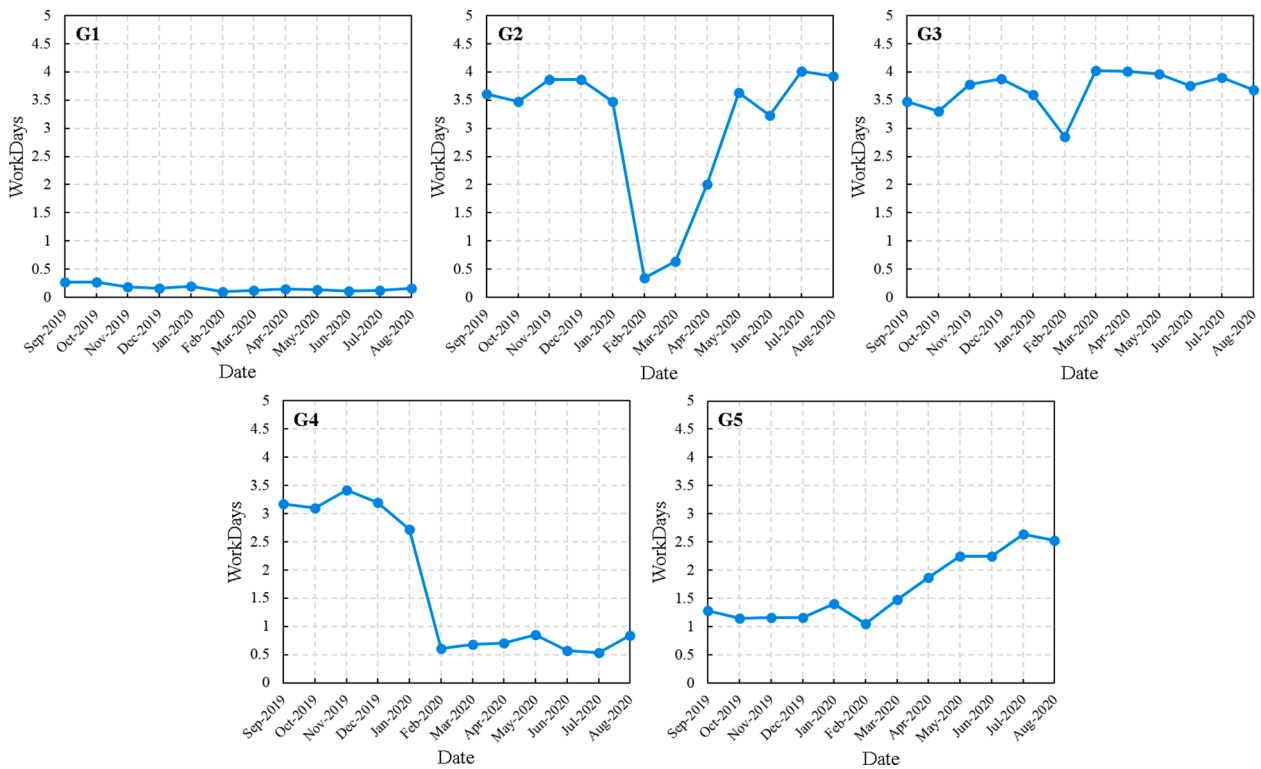


Fig. 10. Clustering results of local residents according to their time series of WorkDays.

Table 9

Number of local residents in different groups clustered by their time series of WorkDays.

Groups	G1	G2	G3	G4	G5	Total
Number of residents (million)	5.55	1.00	0.82	0.60	0.43	8.40
Ratio	66.09	11.85	9.74	7.16	5.15	100%

Table 10

Corresponding relationship between the change pattern of human dwelling intensity at individual scale and at regional scale.

Cluster of dwelling intensity change patterns at regional scale	Group of individuals with different dwelling intensity change patterns
C1 (remained basically unchanged over time)	G2 (local residents who are always in Beijing)
C2 (increased gradually and became stronger than that of before COVID-19)	G2 (local residents who are always in Beijing), G4 (newcomers who came to Beijing after COVID-19), G5 (visitors who came to Beijing before COVID-19)
C3 (decreased first and then gradually recovered to the same level as before COVID-19)	G2 (local residents who are always in Beijing), G6 (migrant residents who left Beijing before COVID-19 and came back after COVID-19 was under control)
C4 (decreased rapidly and has not recovered after COVID-19 was under control)	G2 (local residents who are always in Beijing), G3 (migrant residents who left Beijing before COVID-19 lockdown and have not come back yet)

our study further revealed the heterogeneity of this change in different regions and among different individuals. In fact, different change patterns in different regions indicate the impact of COVID-19 on different urban functions, while different change patterns among different individuals indicate the impact of COVID-19 on different population groups. Both of these two aspects are essential in the development of cities around the world, especially for megacities that with highly mixed urban functions and diversified population composition. In the above

Table 11

Corresponding relationship between the change pattern of human working intensity at individual scale and at regional scale.

Cluster of working intensity change patterns at regional scale	Group of individuals with different working intensity change patterns
C1 (decreased first and then gradually recovered to the same level as before COVID-19)	G2 and G3 (commuters who decreased their commuting times during COVID-19 and reverted to normal after COVID-19 was under control)
C2 (decreased first and then only recovered to half of its level before COVID-19)	G2 and G3 (commuters who decreased their commuting times during COVID-19 and reverted to normal after COVID-19 was under control), G4 (commuters who stopped commuting and have not returned back to work)
C3 (decreased first and then recovered to a level stronger than that of before COVID-19)	G2 and G3 (commuters who decreased their commuting times during COVID-19 and reverted to normal after COVID-19 was under control), G5 (residents who started commuting after COVID-19)
C4 (decreased first and then increased before May 2020, then decreased again due to the second wave of COVID-19)	G2 and G3 (commuters who decreased their commuting times during COVID-19 and reverted to normal after COVID-19 was under control), G4 (commuters who stopped commuting and have not returned back to work)

section, we have illustrated the relationship between these two aspects; in this section, some implications for future urban management will be provided.

First, our findings reveal that dwelling intensity did not increase in all regions as expected. Even though people tended to stay at home after COVID-19 outbreak, dwelling intensity in some regions decreased. The major reasons of this are the departure of migrant workers and students due to the closure of unnecessary industries and schools and the “escape” of urban residents to rural areas due to the higher risk of infection in high density urban areas. The similar phenomenon has been also observed in previous studies conducted in India (Denis, Telle,

Benkimoun, Mukhopadhyay & Nath, 2020) and in Italy (Beria & Lunkar, 2021). In the case of Indian, rural population increased by 7% while cities lost about 4% to 11% of their population (from metropolis to small census towns). In the case of Italy, regional relocation of population during COVID-19 lockdown caused the fall of population in most large cities, especially that in the North, where the outbreak started. Such loss of population in large cities will be a serious social problem in the post-epidemic era, which may cause labor shortages, weaken urban vitality, and reshape the urban fabric. Therefore, appropriate measures should be implemented to minimize its negative impacts.

Second, COVID-19, along with its containment measures reduced working intensity in all regions, but regions with different urban functions showed different degree of recovery after COVID-19 was under control. In most business-related regions, working intensity has recovered to its level before COVID-19, but in some schools, hotels, entertainment venues, and tourist attractions, it has not recovered. This indicates the low resilience of such crowd-gathering urban areas, therefore special attention should be paid in the future urban planning measures to address it. Meanwhile, analysis at individual scale also showed that some people have not returned back to work even though the epidemic has been controlled. This has a twofold explanation: some people lost their jobs during the epidemic and some people converted to remote working after the epidemic. The former may result in social instability and inequality while the latter may, to some extent, relieve traffic pressure. Both of these situations should be noticed in the post-epidemic urban management.

In general, changes in human dwelling and working intensity during the epidemic can be seen as a measurement of urban resilience and sustainability, which to a certain extent, can reveal the problems existed in urban development. By identifying populations that were seriously affected by the epidemic (such as migrant people and people who lost their jobs), targeted policy supports could be implemented to enhance their ability to respond to the impact of such unprecedented public health crisis. By identifying urban regions that were greatly affected by the epidemic and had difficulties in recovering (such as areas with high population density and mobility), micro-environment design and urban function re-configuration could be conducted to reduce the risk of epidemic spread in such regions.

## 7. Conclusion

The changes in human general mobility patterns caused by COVID-19 pandemic have been extensively studied in existing research. However, few studies have investigated the changes in specific human daily activities, which are closely related to different aspects of human life, such as commerce, transportation, employment, environmental impact, and others. In this study, we tracked intensity changes in human dwelling and working over different stages of COVID-19 in Beijing and discussed the mechanism behind these changes. The major conclusions are as follows:

- (1) At regional scale, the changes in human dwelling and working intensity showed different patterns in regions with different urban functions. During COVID-19 outbreak, dwelling intensity remained basically unchanged or even enhanced in most residential and suburb areas but decreased about 40% in some work and education-related areas; working intensity decreased about 60% over the whole city. After COVID-19 was under control, dwelling and working intensity recovered in most regions. However, in schools, hotels, entertainment venues, and tourist attraction related areas, it has not recovered yet and in some cases has even decreased again with the second wave of COVID-19.
- (2) At individual scale, the changes in human dwelling and working intensity showed different patterns among different individuals. As to dwelling intensity, about 43% of residents who dwelled in

Beijing left before COVID-19 lockdown while only 16% have returned back after COVID-19 was under control. As to working intensity, all commuters decreased their commuting times during COVID-19, while only 75% have reverted to normal after the COVID-19 was under control. About 25% of commuters have not returned back to their work and may be unemployed.

- (3) Different combinations of individuals with different dwelling and working intensity changes made up the overall intensity changes presented in different regions. The overlap of the Chinese Spring Festival and the COVID-19 epidemic had a direct influence on each individual's movement behavior and thereby changed their dwelling and working intensity. These changes differentiated among individuals by their different dwelling types and working fields. Furthermore, city regions with different urban functions are usually composed of different types of individuals, therefore, they show different dwelling and working intensity change patterns.

The main significance of this study lies in two aspects. Academically, we constructed an analytical framework to track changes of human daily activities, which can be applied not only in Beijing but also in other cities to evaluate the impact of the epidemic and the city's degree of recovery. In practice, the findings can help governments adopt targeted urban management measures to minimize the negative impact of the pandemic and thereby promote city recovery in the post-pandemic era. Decreased intensity of human dwelling and working may weaken the vitality of a city and thereby slow economic development, therefore, in some regions and industries severely affected by the pandemic, appropriate economic stimulus policy should be implemented to stimulate production and consumption; loss of dwellers and unemployment of workers due to the closure of some food, retail, and entertainment venues may result in instability and inequality in society, therefore, emerging industries, such as e-commerce, remote work, online education, and online entertainment, should be focused on to expand new forms of employment and provide new job opportunities.

However, this study has two limitations. First, only one sample week of data was selected for each month to track human dwelling and working activities, so some detailed changes from week to week within month may be missed. Second, only changes in human dwelling and working activities were analyzed; some other activities, such as shopping, hospital visits, and recreation, which also play an important role in human daily life, were not considered. In the future, more research data should be collected to detect detailed change patterns, and more human daily activities should be analyzed to reveal different aspects of the changes.

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## Declaration of Competing Interest

The authors report no declarations of interest.

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