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Urban greenspace helps ameliorate people’s negative sentiments during the COVID-19 pandemic: The case of Beijing

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A B S T R A C T
The COVID-19 pandemic has had negative effects on people’s mental health worldwide, especially for those who live in large cities. Studies have reported that urban greenspace may help lessen these adverse effects, but more research that explicitly considers urban landscape pattern is needed to understand the underlying processes. Thus, this study was designed to examine whether the resident sentiments in Beijing, China changed before and during the pandemic, and to investigate what urban landscape attributes – particularly greenspace – might contribute to the sentiment changes. We conducted sentiment analysis based on 25,357 geo-tagged microblogs posted by residents in 51 neighborhoods. We then compared the resident sentiments in 2019 (before the COVID-19) with those in 2020 (during the COVID-19) using independent sample t-tests, and examined the relationship between resident sentiments and urban greenspace during the COVID-19 pandemic phases using stepwise regression. We found that residents’ sentiments deteriorated significantly from 2019 to 2020 in general, and that urban sentiments during the pandemic peak times showed an urban-suburban trend that was determined either by building density or available greenspace. Although our analysis included several other environmental and socioeconomic factors, none of them showed up as a significant factor. Our study suggests the effects of urban greenspace and building density on residents’ sentiments increased during the COVID-19 pandemic and that not all green spaces are equal. Increasing greenspace, especially within and near neighborhoods, seems critically important to helping urban residents to cope with public health emergencies such as global pandemics.

1. Introduction

COVID-19, caused by the novel coronavirus SARS-CoV-2 [1], spread rapidly across China and the world after its first detected case in Wuhan in November 2019. By April 16, 2022, the number of confirmed cases of the COVID-19 pandemic is 504.2 million, with 6.2 million deaths, and these figures continue to rise rapidly (https://coronavirus.jhu.edu/map). In response to the COVID-19 outbreaks, national governments worldwide have taken control measures, including the closure of shopping malls, leisure and entertainment places, factories, schools, and many other public places, as well as the lockdowns of entire cities [2–5]. These public health interventions effectively controlled the pandemic’s spread in some countries, but had enormous health, socioeconomic, and environmental consequences [6–10].

A large proportion of COVID-19 patients had depression, anxiety, and post-traumatic stress [11,12]. But the impacts of COVID-19 on human health have gone far beyond those infected [13–15]. The lockdowns and various disease control measures have directly or indirectly impacted the physical and mental health of most, if not all, people around the world [16]. For example, almost all respondents in Chengdu, China considered that their physical health and social-interaction conditions declined during the pandemic [17]. The mental health and psychological well-being of China’s general population deteriorated rapidly in the first two weeks of the pandemic [18]. After the first wave of COVID-19 in Hubei Province, the psychological status of young adults was generally stable, but some were also depressed [19]. The prevalence

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of anxiety and depression varied with the degrees of social isolation, as shown in a study from southwestern China [20]. Social isolation was also associated with a significant increase in depression, anxiety, and stress symptoms in Ireland [21]. Studies have shown that COVID-19-related isolation has had negative psychological effects, such as post-traumatic stress symptoms, confusion, and anger around the world [22].

Conditions of people’s living environment might be correlated with COVID-19’s sentimental and psychological impacts [23]. For instance, a number of studies have shown that urban greenspace has a positive effect on the sentiments of residents as it provides opportunities for residents to get close to nature, have a rest, take physical exercises, and relax their body and mind [3,17,24,25]. Does urban greenspace positively affect residents’ sentiments or psychological wellbeing during extraordinarily trying times such as the COVID-19 pandemic? During the pandemic, people generally reduced both time and scope of outdoor activities all over the world [26–29], but the frequency of visiting nearby greenspace – public lawns and parks in and around neighborhoods – may have increased [30,31]. Thus, urban greenspace may have greater impacts on residents’ physical and psychological well-being during such unusual times. Indeed, a number of studies have reported that greenspace provided positive contributions to self-reported well-being during the COVID-19 pandemic (e.g., Refs. [6,24,32]), with urban parks of greater greenness having more impacts [33]. There is even research showing that simply having quality window views overlooking greenery reduces the risk of depression and severity of anxiety for students [34]. Also, visiting city parks and being immersed in greenspace seem to improve people’s physical and mental health [17,35,36].

Notwithstanding these timely and intriguing studies, it remains unclear how general the ameliorating effects of urban greenspace on residents’ mental health are across environmentally and socioculturally different regions. The simultaneous effects of urban greenspace and other landscape elements (such as roads, buildings, etc.), as well as how they change before and after the COVID-19, have seldom been examined. Thus, we designed this study to address two specific questions: (1) Did the sentiments of urban residents change significantly in 2020 due to COVID-19 as compared to those in 2019 before the pandemic? (2) Did urban greenspace have any positive effects on people’s sentiments during the COVID-19 pandemic in 2020? Note that, while sentiment and emotion are closely related (but distinct) terms, here we use sentiment instead of emotion to be consistent with the name of the technique used in this study – sentiment analysis. We addressed these questions using data from China’s capital, Beijing. Although this study did not directly get to the underlying mechanisms, we also explored the key factors of urban landscape patterns within and nearby neighborhoods and socioeconomic conditions that might simultaneously affect the sentiments of urban residents.

2. Data and methods

2.1. Study area

Beijing, the capital of China, is situated at the tip of the North China Plain and surrounded by mountains to the west, northwest, and north. It has a semi-humid continental climate, characterized by hot and humid summer and dry and cold winter. As the world’s most populous national capital city, Beijing Municipality has a population of about 22 million and a total area of more than 16,410 km\(^2\) within its jurisdiction. Beijing has diverse urban green spaces, including parks, public lawns/open spaces, campus, and neighborhood green areas [37–39]. The total area of public green space is 357 km\(^2\) with a per capita area of 16.6 m\(^2\) [40].

Our study focused on the central area of Beijing, which is demarcated by the 5th Ring Road and covers a total area of 671 km\(^2\) (Fig. 1). The study area accounts for about 4% of the total area of the Beijing Municipality, but hosts nearly 50% of its population. We chose this region as our study area because of the following reasons: (1) it captures the historical and essential urban characteristics of Beijing, and (2) the region inside the fifth ring road has been the study area of a large number of landscape and urban studies (e.g., Refs. [37–39,41]). From 2nd ring road to 5th ring road, the different landscape patterns are reflective of the urban sprawling process and the urban-suburban gradient of Beijing. The coverage of buildings decreased from 26% within 2nd ring road to 19% in 4th–5th ring road, while the coverage of urban greenspace increase from 25% to 35% along this gradient (Fig. S10). Moreover, residents’ park access decreased from 76% in the urban center to 46% in the periphery (in 4th~5th ring road) [42].

2.2. Time series data of the COVID-19 pandemic

The COVID-19 pandemic data in our study were obtained from the official website of the National Health Commission of the People’s Republic of China and the Beijing Municipal Health Commission. At the end of December 2019, “viral pneumonia of unknown cause” was discovered in Wuhan. On January 10, 2020, Wuhan Municipal Health Commission completed the nucleic acid test of the pathogen. From then on, China began to publish COVID-19 pandemic data on a daily basis. In this study, the national daily data of the COVID-19 pandemic covered the period between January 10 and August 31, 2020, while the data for Beijing’s started from January 20 (the time of Beijing’s first confirmed case of COVID-19) to August 31, 2020. This period covered the major changes in the numbers of infected cases and deaths in China during the different phases of the COVID-19 pandemic (Fig. 2A–C).

![Fig. 1. Illustration of the study area, which is the built-up area within the Fifth Ring Road of the Beijing Metropolitan Region. The locations of parks and sampled neighborhoods are indicated.](image_url)
Based on the magnitude and timing of major peaks of COVID-19 cases in China and Beijing (Fig. 2A and B), we divided the study period into five phases (Fig. 2C): (I) Before the first pandemic peak (January 1 ~ January 22, 2020; 22 days), (II) The pandemic peak of China (January 23 ~ April 7, 2020; 76 days), (III) Period between two peaks (April 8 ~ June 13, 2020; 67 days), (IV) The local pandemic peak of Beijing (June 14 ~ July 14, 2020; 31 days), and (V) Post-peak period (July 15 ~ August 31, 2020; 48 days). Wuhan was locked down between January 23 and April 7, 2020. In Beijing, the first COVID-19 high-risk neighborhoods were announced by the Beijing Municipal Government on June 14, 2020, and the last COVID-19 high-risk neighborhoods ended on July 14, 2020. The main reason for distinguishing these time periods was to examine whether people’s sentiments would change before, during, and after a COVID-19 outbreak.

2.3. Data on urban residents’ sentiments

We collected data of residents’ sentiments in response to COVID-19 from the Chinese microblogging website (Weibo.com), which is one of China’s biggest social media platforms. There are 3747 neighborhoods in our study area. We sampled 51 neighborhoods to analyze the residents’ sentiments following two steps. First, we applied a spatially stratified random sampling approach to select neighborhoods and extract their sentiment data. The study area (the five-ring region) was divided into 16 sub-regions according to the five ring roads and four quadrants or ordinal directions (northeast, northwest, southwest, and southeast) (Fig. 1). We randomly selected 10 to 55 neighborhoods in each sub-region considering the size of sub-regions and the number of neighborhoods in the sub-regions. The selection resulted in a total of 494 neighborhoods. Microblogs with points of interest (POIs) tags corresponding to these neighborhoods were extracted. Second, neighborhoods with more than 11 microblogs in each COVID-19 phase in 2020 were retained, resulting 51 sampled neighborhoods in total. The reason for setting the minimum of microblogs to 11 as an inclusion criteria was to balance the dual needs of maximizing the number of sampled neighborhoods and at the same time ensuring an adequate number of microblogs for each sampled neighborhood. To test whether raising this minimum number would affect the outcome of the urban sentiment analysis, we did the same analysis with three alternative minimum numbers (11, 25, and 30), and the results were consistent (see Supplementary Material for details). The spatial distribution of sampled neighborhoods over the study area is shown in Fig. 3.

We obtained a total of 25,357 microblogs with POI tags corresponding to the sampled neighborhoods, including 10,445 microblogs in 2019 and 14,912 microblogs in 2020. Metadata on users’ Weibo locations and posting time were also recorded.

We classified the microblog into three sentimental or sentimental status types, positive, neutral, and negative, according to their text.
Positive and negative sentiments represent, respectively, the expressions of likes and dislikes by the bloggers [43]. The neutral sentiments are sentences stated as a matter of fact without any positive or negative evaluation [43]. We conducted the classification based on text content using the sentiment analysis algorithm provided by Baidu AI Open Platform (https://ai.baidu.com/tech/nlp_apply/-sentimentclassify). The platform calculated probability-based index for three sentimental status types using sentiment analysis based on deep learning and natural language processing [44]. For 1293 microblogs posted with pictures or videos but no text, we manually identified the sentimental status according to the photos or videos of the microblogs. To measure the temporal change of residents’ sentiments in the study area, we calculated the ratio of positive, neutral, and negative sentiment microblogs to the total number of microblogs each day. We denoted them as % Daily Positive Sentiment, % Daily Neutral Sentiment, and % Daily Negative Sentiment. We used them as the indicators of residents’ daily sentiments in this study (more detail available in Supplemental Material). Because the % Daily Neutral Sentiment generally had quite low values (0%–14%), as compared with % Daily Positive Sentiment (48%–100%) and % Daily Negative Sentiment (0%–47%), our analysis focused only on the latter two. To measure the temporal change of sentiment for each neighborhood, we calculated the percent positive and negative sentiments in each neighborhood during each of the five COVID-19 pandemic phases (described earlier) and denoted them as the % Positive Sentiment/Neighborhood/Phase and the % Negative Sentiment/Neighborhood/Phase.

2.4. Data on urban greenspace and socioeconomic factors

To evaluate the potential impacts of urban greenspace on urban residents’ sentiments, we acquired high-resolution (0.5 m) land cover data for the study area [45]. The land cover map was classified from a Pleiades satellite image on September 19, 2015 (resolution of 0.5 m, overall classification accuracy of 92.58%). Urban greenspace parameters were derived from the land cover map. We delineated the boundaries of neighborhoods and urban green spaces based on high-resolution maps from Google Earth (https://earth.google.com/) and Baidu (https://map.baidu.com). The number and total area of parks within 1-km and 2-km buffer zones of neighborhoods were quantified as in Tu et al. [42]. Other urban landscape attributes included greenspace coverage, water bodies, building density, road density, pavement coverage, and accessibility of parks in each sampled neighborhood (Table 1).

In addition, the socioeconomic conditions (e.g., house price, rental price, property management fee, floor area ratio, building type and construction age) of neighborhoods were acquired from the website of Homelink, a Chinese real-estate brokerage company (https://bj.lianjia.com). We manually identified the building type of each neighborhood using images and photos from Google Maps, Baidu Maps, Baidu Street-View, and the Homelink website (more detail on microblog data collection and processing in Supplemental Material).

2.5. Data analysis

To investigate the changes and influencing factors of urban residents’ sentiments before and after the outbreak of the COVID-19 pandemic, including the different stages of the COVID-19 pandemic, we conducted two sets of analyses. The first set of analyses compared the temporal dynamics of residents’ sentiments in 2019 (i.e., before COVID-19) with those in 2020 (i.e., after COVID-19). The second set of analyses aimed to explore the potential impacts of landscape attributes (especially urban greenspace) and socioeconomic factors of neighborhoods on people’s sentiments during different phases of the COVID-19 pandemic in 2020.

We used independent sample t-tests to examine whether there is a statistically significant difference between the means of residents’ daily sentiment before and after the pandemic outbreak. Specifically, we applied the test to 12 paired groups: % Daily Positive Sentiment and % Daily Negative Sentiment in 2020 with those in 2019; % Daily Positive Sentiment and % Daily Negative Sentiment during each of the five COVID-19 pandemic phases in 2020 with those during the same periods in 2019. To help depict the temporal trends, we computed the 15-day moving averages of the daily values of positive and negative sentiments for 2019 and 2020.

We used multiple stepwise regression to analyze the impacts of urban greenspace and socioeconomic factors on the % Positive Sentiment/Neighborhood/Phase and the % Negative Sentiment/Neighborhood/Phase. The same analysis was repeated for each of the five COVID-19 pandemic phases (described earlier), so as to examine possible changes in the relationship between the residents’ sentiments and influencing factors before the first COVID-19 peak, between two adjacent pandemic peaks, and during each peak.

3. Results

3.1. Urban residents’ sentiments before and after the COVID outbreak

Since the total percentage of neutral sentiments were very small (2.8% and 3.1% in 2019 and 2020 respectively), our analysis focused only on positive and negative sentiments (Table S11). Both the percentages of positive and negative sentiments of Beijing residents fluctuated rather substantially on a daily basis with (in 2020) and without (in 2019) the COVID-19 pandemic (Fig. 4). During the study periods (January 1 ~ August 30, 2019; and January 1 ~ August 31, 2020), % Daily Positive Sentiment in 2019 was generally higher than that in 2020 (averaging 74% and 71%, respectively), whereas % Daily Negative Sentiment in 2019 was lower than that in 2020 (averaging 23% and 26%, respectively). The difference between their means was statistically significant (P-value <0.05). These differences in sentiments between the
Table 1: Variables and the assignment rules used in multiple stepwise regression.

| Categorizes                                      | Variables       | Variable explanations                        | Variable types |
|-------------------------------------------------|-----------------|---------------------------------------------|----------------|
| Socioeconomic situation of a neighborhood       | House price     | Average sale price (CNY per square meter)   | Continuous (Price) |
|                                                 | Rental price    | Rent price (CNY per square meter per month) | Continuous (Price) |
|                                                 | Property fee    | Property management fee (CNY per square meter per month) | Continuous (Price) |
|                                                 | Floor area ratio | The ratio of a building’s total floor area to the land parcel area | Continuous (Dimensionless) |
| Building type                                   |                | Types of buildings in neighborhoods, e.g., high-rise towers, and low-rise buildings, e.g., bungalows, low-rise towers, and high-rise buildings | Ordinal (1,2,3,4,5,6) |
| Construction age                                |                | Established time of neighborhoods           | Ordinal (1,2,3,4) |
| Landscape pattern inside a neighborhood         | Green Spaces   | Percentage of green spaces in a neighborhood | Continuous (Dimensionless) |
|                                                 | Building %      | Percentage of building in a neighborhood    | Continuous (Dimensionless) |
|                                                 | Road %          | Percentage of roads in a neighborhood       | Continuous (Dimensionless) |
|                                                 | Pavement %      | Percentage of pavement in a neighborhood    | Continuous (Dimensionless) |
| Landscape pattern of 1 km buffer zone around a neighborhood | Green Space % within 1 km | Percentage of green space in a 1 km buffer zone of a neighborhood | Continuous (Dimensionless) |
|                                                 | Water % within 1 km | Percentage of water in a 1 km buffer zone of a neighborhood | Continuous (Dimensionless) |
|                                                 | Building % within 1 km | Percentage of building in a 1 km buffer zone of a neighborhood | Continuous (Dimensionless) |
|                                                 | Bare Soil % within 1 km | Percentage of bare soil in a 1 km buffer zone of a neighborhood | Continuous (Dimensionless) |
|                                                 | Road % within 1 km | Percentage of roads in a 1 km buffer zone of a neighborhood | Continuous (Dimensionless) |
|                                                 | Pavement % within 1 km | Percentage of pavement in a 1 km buffer zone of a neighborhood | Continuous (Dimensionless) |
| Accessibility of parks around a neighborhood    | Park Count within 1 km | The number of parks in a 1 km buffer zone of a neighborhood | Continuous (Number) |
|                                                 | Park Area within 1 km | The total area of the parks in a 1 km buffer zone of a neighborhood | Continuous (Area) |
|                                                 | Park Count within 2 km | The number of parks in a 2 km buffer zone of a neighborhood | Continuous (Number) |
|                                                 | Park Area within 2 km | The total area of the parks in a 2 km buffer zone of a neighborhood | Continuous (Area) |

* Building types were determined according to Google Map, Baidu Street View, and information on neighborhoods at Homelink website.

** Construction age was grouped into four classes: 1970–1979, 1980–1989, 1990–1999, and 2000–2009.

In addition, the troughs of positive sentiment and the peaks of negative sentiments occurred synchronously, corresponding to the pandemic peak of the entire mainland China and the pandemic peak of Beijing in 2020. In contrast, the sentiments of Beijing residents in 2019 did not show any observable peaks and troughs for the same time periods, with constant fluctuations exhibiting greater daily variability than those in 2020 (Fig. 4).

Furthermore, it is visually evident that the troughs of positive sentiment and the peaks of negative sentiments of Beijing residents corresponded to the spikes of the daily new confirmed cases of COVID-19 in China and Beijing (Fig. 5). In other words, the general temporal pattern of the daily sentiments in 2020 seemed to follow that of the number of daily new confirmed cases of COVID-19. Specifically, during the nationwide pandemic peak, daily new cases and % Daily Negative Sentiment both showed the first peak, and during the pandemic peak in Beijing, they both showed another peak (Fig. 5).

### 3.2. Sentiments during different phases of the COVID-19 pandemic

The average % Daily Positive Sentiment of the five phases of the COVID-19 pandemic in 2020 were generally lower than that in the same time periods in 2019, whereas the average % Daily Negative Sentiment of the five phases in 2020 were higher than that in 2019. In particular, the average % Daily Positive Sentiment during the pandemic peaks of mainland China (January 23-April 7, 2020) and Beijing (June 14-July 14, 2020) was significantly lower than that during the same periods of 2019 (P < 0.001). The average % Daily Negative Sentiment in these phases, on the other hand, was significantly higher than that during the same time periods of 2019 (P-value < 0.001). In addition, the average % Daily Positive Sentiment of the period between the two peaks was significantly lower than that during the same period in 2019 (Fig. 6).

The daily sentiments of Beijing residents during the five COVID-19 pandemic phases in 2020 changed in a way different from that during the same periods in 2019. In 2020, the average % Daily Positive Sentiment showed the highest value in the phase before the first pandemic peak (73.39%), dropped during the pandemic peak time of China (70.23%) and the local pandemic peak in Beijing (68.04%), and rose during the period between two pandemic peaks (70.89%) and post-peak period (71.79%). The average % Daily Negative Sentiment in 2020 changed oppositely. By contrast, before the COVID pandemic, the average % Daily Positive Sentiment during the same five time periods back in 2019 exhibited a generally declining trend, accompanied by a generally increasing trend in the average % Daily Negative Sentiment (Fig. 6).

The spatial pattern of Beijing residents’ sentiments during the different phases of the COVID-19 pandemic in 2020 changed over time, which is visually discernible from the maps of positive and the negative sentiments in sampled neighborhoods for the five COVID-19 pandemic phases in 2020 (Fig. 7). During the pandemic peak of mainland China (January 23-April 7, 2020), the positive sentiment scores in neighborhoods tended to increase from the urban center to the periphery: increasing from 68% within the 2nd ring road to 75% between the 4th and 5th ring roads (Fig. 8). Accordingly, the neighborhood-level scores of negative sentiments decreased from 28% within the 2nd ring road to 23% between the 4th and 5th ring roads (Fig. 8). While during the peak of Beijing’s local pandemic, average % Positive Sentiment/Neighborhood/Phase were higher in the urban center (73% in within the 2nd ring road and 71% in 2nd ~3rd ring road) than in the periphery (67% in 3rd ~4th and 69% in 4th ~5th) (Fig. 8). Accordingly, average % Negative Sentiment/Neighborhood/Phase showed a mirrored pattern.
Fig. 4. Residents’ daily sentiments and their 15-day moving averages in Beijing in 2019 and 2020.

Fig. 5. The daily sentiments of Beijing residents and the daily new confirmed cases of COVID-19 in China and Beijing. (a) residents’ daily sentiments and their 15-day moving averages in Beijing in 2020; (b) the daily new confirmed cases for mainland China; and (c) the daily new confirmed cases in Beijing.
3.3. Correlations between sentiments and landscape attributes and socioeconomic conditions during the COVID-19 pandemic

For the positive sentiment at the neighborhood level, among all the socioeconomic variables considered (house price, rental price, property management fee, floor area ratio, building type, and construction age), only construction age was correlated with people’s positive sentiments and this occurred only during the national pandemic peak phase (i.e., Phase II) (Table 2). Of urban landscape attributes, the percentage of green spaces within a 1 km buffer around a neighborhood was significantly correlated with the % Positive Sentiment/Neighborhood/Phase during the peak of Beijing pandemic (Phase IV). Building density within a 1 km buffer around the neighborhood was also correlated with the positive sentiment in the neighborhood during the first three phases of the COVID-19 pandemic (Adjusted $R^2$ ranged from 11% to 22%). On a more local scale, the positive sentiment was significantly correlated with within-neighborhood road density, but not with greenspace coverage, building density, and pavement coverage at Phase I, II and III. No correlation was observed during the post-peak phase between people’s positive sentiment and landscape attributes within or around neighborhoods. Of the five pandemic phases, the nationwide pandemic peak phase had the strongest correlation (Adjusted $R^2$ was 0.216) (Table 2).

For the negative sentiment at the neighborhood level, the correlation results almost mirrored those for the positive sentiment (Table 3). The effect size (adjusted $R^2$) of landscape attributes and socioeconomic conditions was generally similar to that for positive sentiments, but the signs of the correlation pointed to the opposite directions (Table 3). On exception, though, was that the number of parks within 2 km around a neighborhood was negatively correlated with the % Negative Sentiment/Neighborhood/Phase (but not correlated with the % Positive Sentiment/Neighborhood/Phase).

4. Discussion

4.1. Did the sentiments of urban residents in Beijing change significantly before and after the COVID-19 outbreak?

Our study found that residents’ sentiments in Beijing deteriorated significantly during the COVID-19 pandemic in 2020 as compared to the pre-pandemic conditions, especially during the nationwide pandemic peak and Beijing’s pandemic peak (Figs. 4 and 6). Previous studies reported that respondents suffered from mental health problems, such as anxiety, depression, and distress during the COVID-19 pandemic [15,46,47], based on interviews or surveys after the pandemic outbreak. The perception of risk [48], reduction of physical activities [5], and social distancing [17] were identified as potential pathways through which COVID-19 impacted residents’ sentiment. Our results corroborated these earlier findings with more detailed information on the spatial pattern.
and temporal dynamics during the different pandemic phases with multiple peaks. A strength of our study was the direct comparison of residents’ sentiments before and after the COVID-19 pandemic outbreaks. We used sentiment analysis based on social media data to quantify residents’ sentiments, which enabled us to detect the differences in the levels and temporal trends of residents’ sentiments before the first outbreak of the COVID-19 pandemic and during its different development phases. The results of this before-after comparison (Figs. 4 and 6), as well as the synchronous change of residents’ sentiment with daily new confirmed cases of COVID-19 (Fig. 5), provide empirical evidence that the changes in residents’ sentiments were not seasonal fluctuations but consequences of the pandemic. It is worth noting that residents’ sentiments rebounded to some extent after the nationwide and Beijing pandemic peaks. Especially after the Beijing pandemic peak (i.e., the post-peak period), the levels of residents’ positive and negative sentiments were not statistically significantly different from those in the same time periods in 2019. This may have been a result of the combined effects of people’s resilience to abrupt disturbances and related governmental policies.

4.2. Did urban greenspace have any effects on people’s sentiments during the COVID-19 pandemic?

Our results showed that during the COVID-19 pandemic, the positive impact of urban green spaces on residents’ sentiments increased (Tables 2 and 3). Previous studies reported the positive effects of urban greenspace on residents’ mental health or sentiments [49–53]. But the importance of greenspace, as compared with other landscape attributes, during the COVID-19 pandemic is not well understood. Our study found that people’s sentiments were affected by the construction age of the neighborhood, and building density and greenspace coverage surrounding the neighborhood. Moreover, their effects differed across Phase I to IV of the COVID-19 pandemic. Specifically, building density in

Fig. 7. Changes in the spatial pattern of Beijing residents’ sentiments in all sampled neighborhoods during the different phases of the COVID-19 pandemic in 2020. The maps of % Neighborhood-phase Positive Sentiment (1st row) and % Neighborhood-phase Negative Sentiment (2nd row) each correspond to the five COVID-19 pandemic phases in 2020 (columns). The mean and standard deviation were denoted below each map. The size of the circle is proportional to the values of the neighborhood-phase sentiments.

Fig. 8. Residents’ sentiments during the different phases of the COVID-19 pandemic in the sub-regions demarcated by the ring roads (within 2nd, 2nd~3rd, 3rd~4th, and 4th~5th). The means of % Neighborhood-phase Positive Sentiment (a) and % Neighborhood-phase Negative Sentiment (b) are shown, with error bars denoting standard deviation. The time duration of each phase is denoted below the x-axis.
### Table 2
Multiple stepwise regression results for identifying factors affecting residents’ positive sentiments during different phases of the COVID-19 pandemic.

| Categories | Variables | Standardized Coefficients |
|------------|-----------|----------------------------|
|            |           | Phase I, 1/1-1/22 | Phase II, 1/23-4/07 | Phase III, 4/08-6/13 | Phase IV, 6/14-7/14 | Phase V, 7/15-7/81 |
|            |           |                      |                      |                      |                      |                      |
|            | Socioeconomic situation of a neighborhood | House price / Rental price / Property management fee / Floor area ratio / Building type / Construction age / | / / / / / / | / / / / / / | / / / / / / | / / / / / / |
|            | Landscape pattern inside a neighborhood | Green Spaces % / Building % / Road % / Pavement % / | / / / / | / / / / | / / / / | / / / / |
|            | Landscape pattern of 1 km buffer zone around a neighborhood | Green Spaces % within 1 km / Water % within 1 km / Building % within 1 km / Bare Soil % within 1 km / Road % within 1 km / Pavement % within 1 km / | / / / / / / | / / / / / / | / / / / / / | / / / / / / |
|            | Accessibility of parks around a neighborhood | Park Count within 1 km / Park Area within 1 km / Park Count within 2 km / Park Area within 2 km / | / / / / | / / / / | / / / / | / / / / |
| Adjusted $R^2$ | | 0.189 | 0.216 | 0.111 | 0.106 | / | |
| F value | | 6.818 | 7.900 | 7.264 | 6.921 | / | |
| P value | | 0.002 | 0.007 | 0.010 | 0.011 | / | |
| N | | 51 | 51 | 51 | 51 | 51 | 51 |

Note: * and ** represent that the coefficients are significant at the 0.05 and 0.01 level (2-tailed).

### Table 3
Multiple stepwise regression results for identifying factors affecting residents’ negative sentiments during different phases of the COVID-19 pandemic.

| Categories | Variables | Standardized Coefficients |
|------------|-----------|----------------------------|
|            |           | Phase I, 1/1-1/22 | Phase II, 1/23-4/07 | Phase III, 4/08-6/13 | Phase IV, 6/14-7/14 | Phase V, 7/15-7/81 |
|            |           |                      |                      |                      |                      |                      |
|            | Socioeconomic situation of the neighborhood | House price / Rental price / Property management fee / Floor area ratio / Building type / Construction age / | / / / / / / | / / / / / / | / / / / / / | / / / / / / |
|            | Landscape pattern inside the neighborhood | Green Spaces % / Building % / Road % / Pavement % / | / / / / | / / / / | / / / / | / / / / |
|            | Landscape pattern of 1 km buffer zone around a neighborhood | Green Spaces % within 1 km / Water % within 1 km / Building % within 1 km / Bare Soil % within 1 km / Road % within 1 km / Pavement % within 1 km / | / / / / / / | / / / / / / | / / / / / / | / / / / / / |
|            | Accessibility of parks around a neighborhood | Park Count within 1 km / Park Area within 1 km / Park Count within 2 km / Park Area within 2 km / | / / / / | / / / / | / / / / | / / / / |
| Adjusted $R^2$ | | 0.164 | 0.226 | 0.121 | 0.162 | / | |
| F value | | 5.893 | 8.293 | 7.856 | 5.818 | / | |
| P value | | 0.005 | 0.001 | 0.007 | 0.005 | / | |
| N | | 51 | 51 | 51 | 51 | 51 | 51 |

Note: * and ** represent that the coefficients are significant at the 0.05 and 0.01 level (2-tailed).
a neighborhood’s vicinity had a negative correlation with residents’ positive sentiments before Beijing’s pandemic peak, and this correlation became stronger after the outbreak of the nationwide pandemic. During the Beijing’s pandemic peak, however, building density was no longer significant, and urban greenspace in a neighborhood’s vicinity became the only landscape feature affecting residents’ sentiments. Overall, our study indicates that both urban greenspace and building density surrounding a neighborhood were important to residents’ mental health during the COVID-19 pandemic.

The greater effects of urban greenspace during the pandemic peaks might result from the increase in residents’ use of urban greenspace. Urban green spaces near neighborhoods became more important for residents’ physical activities due to the control measures of the COVID-19 pandemic [54]. In Beijing, for example, during the peak periods of the pandemic, unessential business services and community facilities were closed, such as shopping malls, cinemas, and restaurants. Large parks were closed or opened with a limit of visitors. Neighborhoods with high risk of contagion were told to quarantine at home. Residents in medium and low-risk neighborhoods could still go out, but they tended to visit only nearby places. Therefore, the green spaces in and around their neighborhoods became primary places for outdoor activities and social activities. A study in Brisbane, Australia [55] found that 36% of respondents increased their use of urban greenspace, and 45% of those who did not previously use urban greenspace began to do so during the pandemic.

Within-neighborhood road density was negatively correlated with positive sentiment before the pandemic, but the correlation disappeared during the pandemic. This may be attributable to the fact that there was essentially no traffic on the road during the pandemic. In general, neighborhood construction age, building density, and road density may act as proxy variables for neighborhoods’ socioeconomic status, transit use, and land-use mix [56,57] which indirectly impact residents’ sentiments. During the pandemic peak times, however, urban greenspace may act as a direct factor influencing residents’ sentiments. More studies are needed to better understand the underlying mechanisms of these direct and indirect effects.

The spatial pattern of residents’ sentiments may also be explained by the different effects of landscape attributes, especially urban greenspace. For example, during the national pandemic peak, building density and neighborhood construction age were identified as potential sentiment-influencing factors (Tables 2 and 3). Thus, decreasing building density and decreasing construction age along the urban-suburban gradient might be important factors for the observed increasing trend of positive sentiment (Fig. 8a; Phase II) and decreasing trend of negative sentiment (Fig. 8b; Phase II) from the urban center outward. However, during the Beijing pandemic peak, the trends of positive sentiment and negative sentiment were reversed along the urban-suburban gradient (Fig. 8; Phase IV). During this phase, greenspace was the only landscape attribute that was correlated with sentiments (Tables 2 and 3). An earlier study showed that the neighborhood park access decreased along the urban-suburban gradient [42]. Thus, the contrasting spatial pattern of positive and negative sentiments across the ring roads during the Beijing pandemic peak might be due, at least partly, to accessible greenspace. These results indicate that the landscape features that influenced people’s sentiments in Beijing varied with the pandemic phases and the epicenter locations. Yet, because building density is usually negatively correlated with greenspace area, our results clearly show that greenspace played a more important role in lifting up the sentiments of Beijing residents during the pandemic than all other environmental and socioeconomic factors considered in this study.

4.3. Implications and future directions

Numerous studies in recent decades have shown that urban landscape composition and configuration, especially greenspace-related attributes, affect the psychological and physical wellbeing of residents in many ways [58,59]. Our study suggests that the positive impacts of urban greenspace, as well as the negative effects of building density, on residents’ mental health may be further enhanced during public health emergencies, such as the COVID-19 pandemic. Unfortunately, in the face of climate change, rapid urbanization, and deteriorating ecosystems around the world, public health emergencies are expected to increase in frequency. Thus, an obvious and important implication of our study is to increase greenspace and decrease building density so as to increase urban resilience. This sounds like a cliché, but our results suggest that simply increasing the total coverage of greenspace for a city like Beijing may not achieve the intended purposes. Large and spectacular parks bring honor and fame to a city and health benefits to its residents, but available green spaces within walking distance of neighborhoods seem more relevant during such emergency times, as indicated by our findings. Beijing government built more than 50 pocket parks and mini green spaces (less than 1 ha in area) in 2021 [60] mostly in densely built area in order to improve green space accessibility. In addition, limiting building density to a certain level should also be considered as a way of ensuring healthy living environment for people [61], especially for megacities like Beijing. Balancing and improving the relationship between building density and greenspace is a grand challenge and opportunity for urban resilience and sustainability in years to come, which relies on the integration of ecological, geographic, and design sciences [62–64].

Based on our study, there are some interesting and important research directions for the future. In particular, sentiment analysis was based on extracted information from microblogs, but the individuals who frequently write microblogs are not necessarily representative of the whole population of the city. For example, studies have shown that young people seem more likely to use social media platforms [65,66]. Also, it is possible that the COVID-19 pandemic may have differentially impacted the mental health of different social groups. In central China, for instance, the levels of anxiety and depression were found to be higher among economic migrants, people aged between 18 and 30 and over 60, and people with higher education [67]. However, it is currently challenging to identify the socioeconomic information of users from the microblogging websites. To alleviate the potential problem, we included neighborhood socioeconomic variables in regression analysis to reduce possible errors due to sampling biases. In general, though, how well such microblog-based data actually represent the general population and people’s sentiments is an urgent and important research topic as bigdata and machine learning are becoming a primary approach to the study of urban emotions/sentiments [25,68,69]. Toward this end, a first step is to obtain metadata on the users of social media platforms and micro-bloggers, such as their socioeconomic and demographic characteristics.

5. Conclusions

Through sentiment analysis based on the social media data, we found that the sentiments of Beijing residents were generally worsened in 2020 due to the COVID-19 pandemic. The decline of positive sentiment and the increase in negative sentiment were especially evident during the peak times of the pandemic. Also, these urban sentiments exhibited some spatial patterns: during the nationwide pandemic peak, Beijing residents’ sentiments got better from the urban center to the urban periphery possibly because of decreasing building density. During the Beijing pandemic peak, however, people’s sentiments tended to be worse from the urban center to the urban periphery possibly because of decreasing available green spaces. Overall, our study suggests that during the COVID-19 pandemic, the impacts of landscape attributes, especially greenspace and building density, on the sentiments of urban residents increased. These findings have useful implications for the design and management of cities, so as to enhance urban resilience to public health emergencies through greenspace and building planning.
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.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.buildenv.2022.109449.

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