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Gauging urban resilience in the United States during the COVID-19 pandemic via social network analysis

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ABSTRACT

Social distancing policies and other restrictive measures have demonstrated efficacy in curbing the spread of the COVID-19 pandemic. However, these interventions have concurrently led to short- and long-term alterations in social connectedness. Comprehending the transformation in intracity social interactions is imperative for facilitating post-pandemic recovery and development. In this research, we employ social network analysis (SNA) to delve into the nuances of urban resilience. Specifically, we constructed intricate networks utilizing human mobility data to represent the impact of social interactions on the structural attributes of social networks while assessing urban resilience by examining the stability features of social connectedness. Our findings disclose a diverse array of responses to social distancing policies regarding social connectedness and varied social reactions across U.S. Metropolitan Statistical Areas (MSAs). Social networks generally exhibited a shift from dense to sparse configurations during restrictive orders, followed by a transition from sparse to dense arrangements upon relaxation of said orders. Furthermore, we analyzed the alterations in social connectedness as demonstrated by network centrality, which can presumably be attributed to the rigidity of policies and the inherent qualities of the examined MSAs. Our findings contribute valuable scientific insights to support informed decision-making for post-pandemic recovery and development initiatives.

1. Introduction

The coronavirus disease 2019 (COVID-19) pandemic not only poses a significant threat to human life but also challenges public health governance and the management of national economic departments (Sohrabi et al., 2020). The World Health Organization (WHO) declared COVID-19 a pandemic on March 11, 2020, and as of May 2022, more than 6 million deaths have been reported. To curb the spread of the highly contagious epidemic, authorities have implemented social distancing policies, including stay-at-home orders and travel restrictions. Studies have shown that social distancing policies are effective in controlling the spread of COVID-19 (Anderson et al., 2020; Bai et al., 2020).

However, social distancing policies have affected social connectedness, which is related to social stability. Stay-at-home orders limit social mobility in cities and make it difficult for non-essential businesses to survive, which poses economic challenges (Bavel et al., 2020; Huang et al., 2021; Huang, Bao, Li, Zhang, & Zhao, 2023; Ritter & Pedersen, 2020). Studies have shown that stay-at-home orders are associated with increased occurrences of violent crimes, unemployment, and other social problems (Beland, Brodeur, & Wright, 2020; Li, Huang, Li, & Xu, 2022). As COVID-19 is still present, epidemic prevention and control are bound to enter the normal stage, threatening social security and stability. Therefore, it is essential to assess and understand the resilience of the urban system during the pandemic to ensure the operation of the complex urban system.

The resilience of complex systems can be measured by evaluating their ability to resist and recover from disturbances. Resistance refers to

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a system's capacity to endure disturbances and their adverse effects, while recovery pertains to a system's ability to assimilate disturbances and return to a new stable state (Cutter et al., 2008). The assessment of resistance and recovery is often used to gauge the stability of ecosystems exposed to various disturbances, such as droughts, floods, and fires. For instance, in a study conducted by Hoover, Pfennigwerth, and Duniway (2021), the resistance and resilience of plant communities were quantified during drought treatments, revealing the mechanisms by which drought disturbances affect the stable state of the plant community.

In recent years, resilience has been introduced into the fields of urban planning and urban disaster management (Kammouh et al., 2019; Liao, 2012). Liao (2012) developed an urban resilience theory aimed at reducing the risk of urban floods. This theory defines urban resilience to floods as the capacity to withstand flooding and reorganize in the face of physical and socioeconomic disruptions. Chen et al. (2020) developed a quantitative evaluation model of urban resilience based on the theory of resilience, where social factors affecting urban resilience were analyzed in combination with Typhoon Morakot. Meanwhile, Wang et al. (2021) applied resilience theory to study the influencing factors of economic development in Kunming City and proposed countermeasures to promote better urban development. The study of resilience can inspire ideas for urban safety and sustainable development, which has significant practical implications for improving the efficiency of governmental public management.

Measuring resilience during the COVID-19 pandemic is challenging, as it is not a directly observable phenomenon, and its evaluation relies on proxy variables. Coarse temporal scales, such as annual or quarterly changes in economic indicators, can reflect the impact of disasters on cities (Rose, 2007), but may not reveal their adaptive and dynamic adjustment ability. Research has shown that urban economic development is closely linked to social connectedness (Yaish & Andersen, 2012), which can be better characterized by fine-grained big geographical data, including mobile device data, social media data, and GPS signaling data (Di Clemente et al., 2018; Huang, Li, Jiang, et al., 2020; Li et al. 2021; Liu et al., 2023). Such data can provide valuable insights into the functioning of social networks and help understand how urban populations respond to pandemics or other disasters.

Social networks have become a valuable tool for understanding geospatial interactions. Regular networks, such as mesh topology and ring topology, typically connect each node to its neighbors (Antonio & Indratno, 2021; Huang, Lu, et al., 2022). In contrast, complex networks refer to networks with nontrivial topological characteristics that exhibit more randomness than regular networks (Zhou et al., 2022). For instance, a small world model is a complex network constructed by randomly rewiring links of a regular network (Vragović, Louis, & Díaz-Guilera, 2005). Complex networks can serve as mathematical models to evaluate urban resilience by describing spatial interactions. The study of the structural characteristics and evolution patterns of social networks has become an emerging trend in disaster management and urban planning (Karunarathne & Lee, 2020a; Therrien, Jutras, & Usher, 2019). For example, Karunarathne and Lee (2020b) constructed a social network based on questionnaires to qualitatively describe the prevention and recovery process of floods in rural areas. In recent years, researchers have combined big geographic data and social network analysis methods to study social connectedness. For example, Walsh and Pozdnoukhov (2011) identified the community structure in the city through social network analysis using mobile phone call record data. Shi et al. (2016) explored the influence of spatial and temporal factors on social networks based on the structural characteristics of mobile phone data and social networks.

In this study, we seek to answer two critical questions: 1) What are the features of the resilience of social networks amid the pandemic? 2) What are the evolution patterns of social networks in response to the pandemic? To answer these two questions, we leveraged social network analytics to examine the pandemic's impact on society. We began by constructing a complex network using social mobility data and analyzing the response of social interaction to social distancing measures. We then applied resilience theory to evaluate urban resilience to the COVID-19 pandemic and explore its characteristics. Finally, we examined structure evolution patterns via network centrality measures. Our study's findings can help government authorities understand the pandemic's trends better and other disruptive events and provide scientific references to support post-pandemic recovery and development.

2. Study area and data

To study urban resilience during the COVID-19 pandemic, we focus on metropolitan statistical areas (MSAs) as they typically implement similar social distancing policies (Huang, Li, Lu, et al., 2020; Huang, Zhao, et al., 2022). An MSA is defined as an area that includes at least one urbanized region with a population of at least 50,000. In our study, we selected thirty of the most populous MSAs based on the MSA Population Totals in 2019 (see Fig. 1). These MSAs include Atlanta, Austin, Baltimore, Boston, Charlotte, Chicago, Cincinnati, Dallas, Denver, Detroit, Houston, Las Vegas, Los Angeles, Miami, Minneapolis, New York, Orlando, Philadelphia, Phoenix, Pittsburgh, Portland, Riverside, Sacramento, San Antonio, San Diego, San Francisco, Seattle, St. Louis, Tampa, and Washington D.C.

To conduct our study, we utilized mobile records made publicly available by SafeGraph (https://www.safegraph.com/) from January 1, 2019, to April 16, 2021, encompassing a total of 837 days. SafeGraph aggregates observed mobile records to the Census Block Group (CBG) level and produces origin-destination (OD) records on a daily basis. To ensure data reliability, we excluded CBG information with less than five devices visiting that CBG per month. To determine sampling rates, we calculated population and mobile device records in each Metropolitan Statistical Area (MSA). The overall sampling rate was approximately 5.44 %, which varied across different cities. For instance, the average sampling rate of Charlotte was 6.95 %, while that of San Francisco was 3.67 %. For more information on sampling rates and their temporal changes, please refer to Fig. S1 in the Supplementary Materials. We followed the same mobile record processing procedure as described by Li et al. (2021). The OD matrices we constructed based on the mobility patterns of CBG-level users (Li et al. 2021) provide a good representation of population flow within MSAs.

3. Methodology

In this study, we employed social network analysis to assess urban resilience and examine the evolution pattern of spatial structure. First, we constructed social networks that depict social connectedness based on complex network theory. We analyzed changes in the structural characteristics of social networks in each MSA to reflect the impact of the COVID-19 pandemic on human mobility. Furthermore, we explored the degree of loss and recovery of interactions in each MSA. Lastly, we utilized the centrality of the social network to investigate spatiotemporal evolution patterns of urban spatial structures during the COVID-19 pandemic. Fig. 2 illustrates the overall workflow of our study.

3.1. Social network construction and investigated network properties

Social network analysis consists of a group of methods used to understand and analyze social connectedness (Scott, 1988). We first constructed a complex network reflecting spatial interactions in each MSA. In this study, the CBG region where the mobile devices are located is mapped as node V of the network, and the connection between regions is also mapped into the network. Given the number of mobile devices flowing from the region V_i to region V_j as n, there exists an edge V_{ij} in the social network with n as the weight value.

The time series of network structural characteristics can be observed to understand the impact of the COVID-19 pandemic on spatial connections. The network's average degree and network's density are

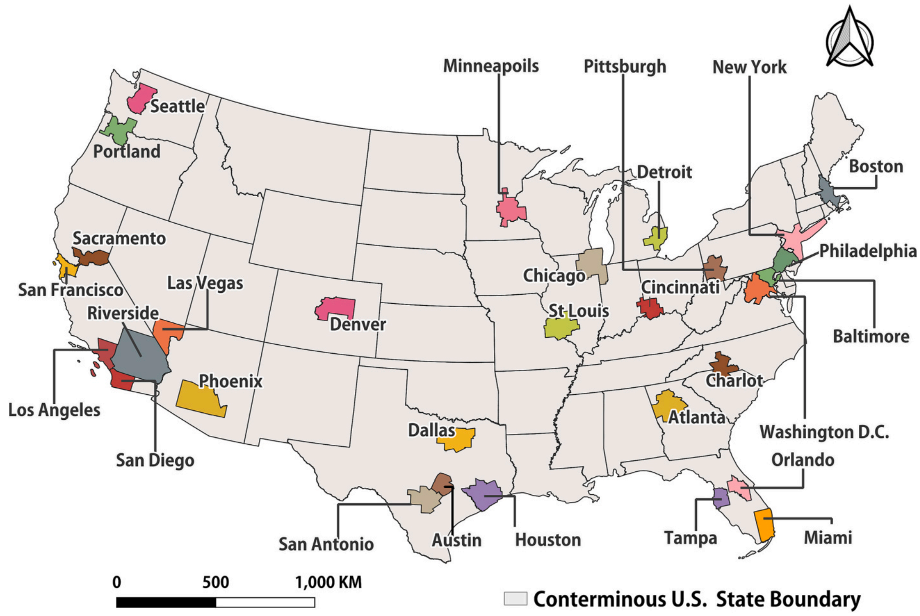

Fig. 1. Distribution of the top thirty most-populated MSAs in the United States.

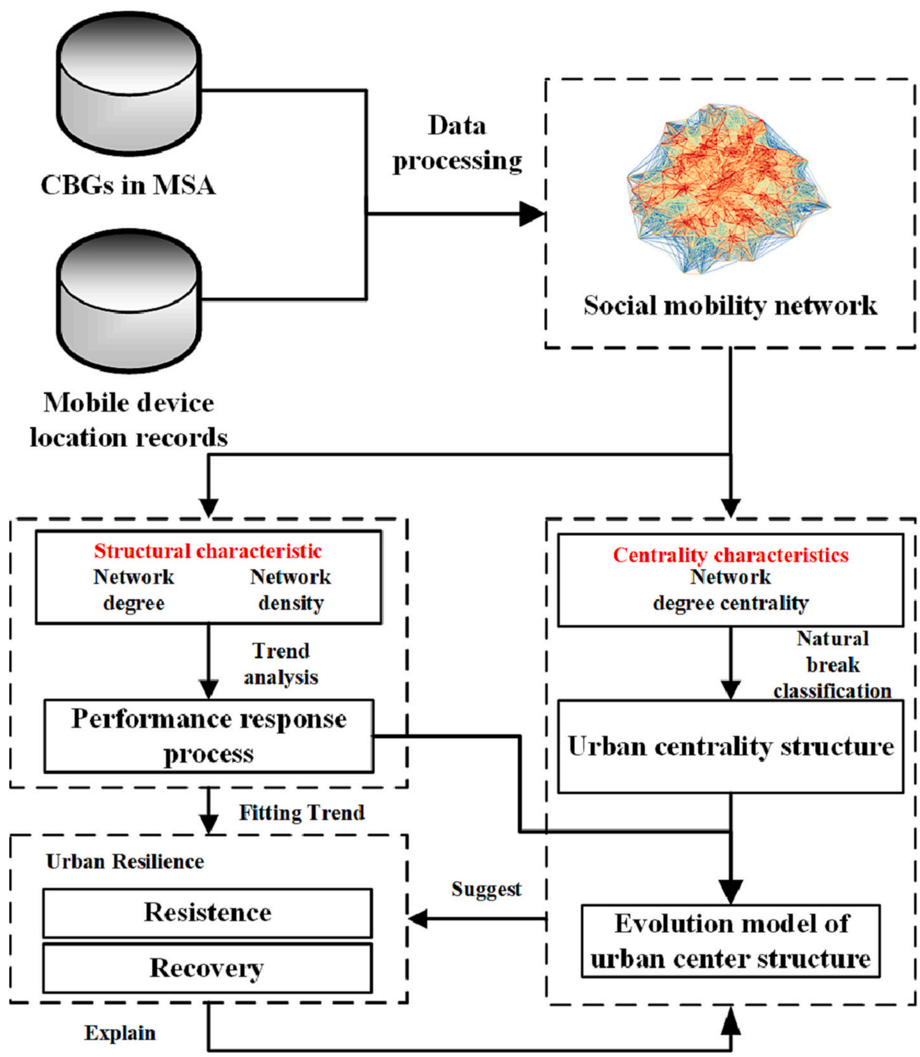

Fig. 2. The employed complex network analytic framework.

important attributes that reflect the structural features of networks (Rachman & Maharani, 2013; Yuan et al., 2018). The average degree denotes the average of the degrees of all nodes in the network. The larger the network average degree value is, the more active the spatial interactions are within the MSA. Network density represents the ratio between the actual ties in the social network and all possible ties, which indicates the intensity of spatial connections in a social network. The higher the value is, the stronger the spatial interactions are within the MSA. The average degree of network and network density are formulated following Eqs. (1)–(3):

$$Degree\ (G) = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N}\left(w_{ij}x_{ij}\right)}{N} \tag{1}$$

$$L = \sum_{i=1}^{N}\sum_{j=1}^{N}\left(x_{ij}\right) \tag{2}$$

$$Density\ (G) = \frac{L}{N(N-1)} \tag{3}$$

where N denotes the total number of nodes in the network and w_{ij} denotes the travel amount of nodes flowing from region V_i to region V_j. x_{ij} denotes a value of either 0 (no connection between V_i and V_j) or 1 (there is a connection between V_i and V_j). L is the number of edges in network G, and N is the value of nodes in the network. We constructed weekly networks of each MSA for a total of 119 weeks.

3.2. Evaluating social network resistance and recovery

During the COVID-19 pandemic, the spatial interaction ties have been significantly weakened by epidemic prevention and control policies and individuals' willingness (Bavel et al., 2020; Ritter & Pedersen, 2020). In this study, we used the network average degree to estimate the steadiness of social networks. As human mobility is periodic and repetitive (Hasan, Zhan, & Ukkusuri, 2013), we took the week as the basic temporal unit. The network average degree in a week of the social network was averaged as the state value of the social system. In addition, due to the differences in social background characteristics in different regions, we used the Z score method to standardize the sequences of network average degrees, where the mean value of the network average degree from January 1, 2019 to March 7, 2020 was selected as control. For the time series of standardized social system state values, urban resilience is defined graphically as the normalized shaded area underneath the functionality function of a system (Cimellaro, Reinhorn, & Bruneau, 2010). Urban resilience has two dimensions, i.e., urban resistance and recovery. Urban resistance and recovery indicators can be obtained by calculating the deviation of social system attributes from their typical behavior (control group). In this study, urban resistance Ω describes the degree of damage to the social network from disruptive disturbances, while urban recovery Δ describes the degree of recovery from the degraded state to the new stable state after the disturbance is attenuated or eliminated. For a single event, the resistance and recovery indicators (Cimellaro et al., 2010) are given as follows (Cimellaro et al., 2010):

$$\Omega = \int_{i}^{x}\left(f(t) - f(t=i)\right)\frac{d(t)}{(x-i)} \tag{4}$$

$$\Delta = \int_{x}^{j}\left(f(t=x) - f(t)\right)\frac{d(t)}{(j-x)} \tag{5}$$

where $f(t)$ is a function of a segmented linear fit to the trend of social network changes. i represents the time of the social network from pre-interference to the damaged period; x represents the time when the social network starts to recover; and j represents the time when the social network transitions from the recovery period to the stable period. In this study, we unified the social network transition dates of selected MSAs. The social network trends obtained in Section 3.1 are referred to when specifying i, x, and j. We acknowledge the existence of trivial differences in transition dates and do not believe such trivial differences will affect the subsequent analyses.

3.3. Extracting spatiotemporal evolution patterns of social networks

The centrality metrics of social networks aim to measure the influence of nodes in social networks (Misra et al., 2017). Commonly used metrics for social network centrality include degree centrality, closeness centrality, and betweenness centrality, among which degree centrality is the most commonly used measure. The degree centrality of nodes reveals the spatial evolution of social networks during the disturbance period. When comparing different social networks, standardized degree centrality is often used as a standardized measure. The calculation of the degree centrality of a node follows:

$$d_i = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N}\left(x_{ij}\right)}{N-1} \tag{6}$$

Regions with a high degree centrality may exhibit better decision-making efficiency and play a crucial role in network stability compared to regions with low centrality (Misra et al., 2017). Extracting spatiotemporal evolution patterns of highly centralized nodes can offer insights into the resilience of social mobility networks. In this study, we first calculated the average degree centrality in each MSA during three different periods: non-strict control, strict control, and less strict control. We then applied the natural breaks method to classify nodes' importance levels, where nodes with the highest degree centrality level represent core regions. We measured the distance between the core regions and the center of the standard deviation ellipse that contains all core CBG regions to explore their spatial distribution. We employed a combination of violin plots, box plots, and density traces to examine the distribution characteristics of distance values. The violin plot displays the distance distribution, reflecting the aggregation structure of the core region. Comparing the peak values of distance distributions in different periods helps us better understand each MSA's urban resilience. We also summarized the spatiotemporal evolution patterns of spatial structures in each MSA, providing useful references for local governments to assess both the short- and long-term impacts of the COVID-19 pandemic.

4. Results

4.1. The responses of social connectedness to restrictive policies

The structural characteristics of social networks demonstrate the consistency of social connectedness and social distancing policies, as depicted in Fig. 3. For each MSA, two main response processes can be identified based on the trends in social network structural characteristics. During the response process, social networks tend to become sparser and then denser, while preventive and control measures are initially strengthened and then relaxed. The first response occurred around March 11, 2020, when the WHO declared COVID-19 a pandemic and the United States declared a national emergency. The government's implementation of strict social distancing policies in response to the severe COVID-19 pandemic situation led to the closure or limited capacity of public places such as restaurants and stores, resulting in decreased spatial connections. On April 9, 2020, the president announced “Opening Up America Again” guidelines, and the social network shifted from resistance to the recovery process. This shift was likely a political response to the high unemployment rate (Zhang & Warner, 2020), which enabled enterprises to resume work and production and led to increased interactions within public places. The network characteristics remained relatively flat from June 1, 2020, to

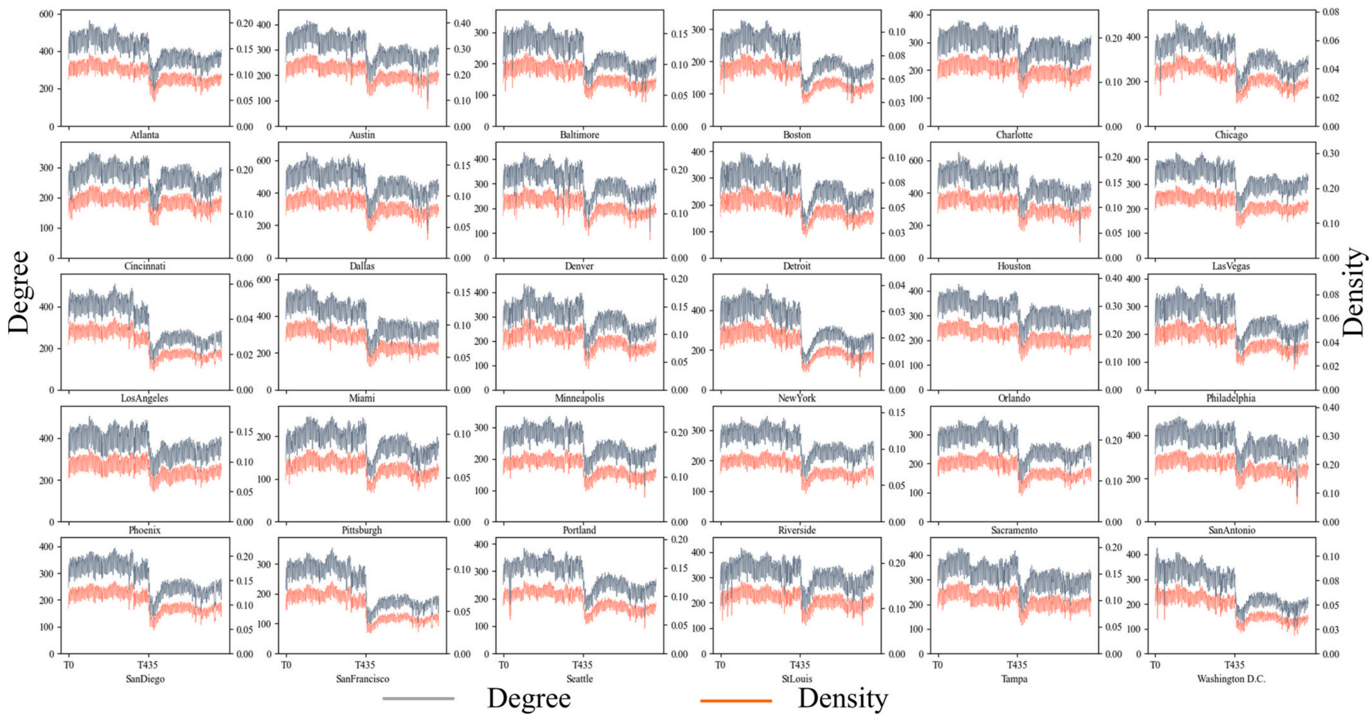

Fig. 3. Dynamics of social network structure features (T0: January 01, 2019; T435: March 11, 2020).

mid-November 2020. The second response followed the CDC's statement about reducing travel for the Thanksgiving holiday on November 19, 2020. According to Reuters, as of November 2020, most U.S. states and cities had implemented varying degrees of epidemic prevention restrictions, such as wearing masks or suspending reopening plans, resulting in a downward trend in social network characteristics. As of February 7, 2021, with the number of new outbreaks decreasing and vaccinations progressing, governmental measures are being relaxed, and social networks are gradually recovering. Although changes in social networks may lag behind policy enactment, social network structural patterns effectively capture spatial interactions in response to policies.

Regarding the magnitude of change in the two response processes of the social network, we observe that the magnitude of change in the second response is comparatively smaller, implying that the society made more adaptations. The adaptive changes in the social system can be explained from two aspects. The first explanation is the relaxation of prevention and control policies, such as allowing more transportation and permitting dining at restaurants. The other explanation is the fatigue of COVID-19-based restrictive orders among the population. Fig. S2 in the Supplementary Materials shows the average network density of the social networks for all MSAs.

4.2. *Evaluation of urban resilience*

In order to comprehensively evaluate the extent of loss and recovery of each MSA during the COVID-19 pandemic, the resistance and recovery of the network were analyzed by determining the overall trend of the network average degree, as shown in Table 1. The computed results of resistance and recovery are found to be consistent with the variation range of social network structural characteristics. Furthermore, in line with the patterns observed in Fig. 1, it is notable that the difference between the absolute value of resistance and recovery reduced during the second response.

In addition, during the second response phase, the recovery of Atlanta, Austin, Charlotte, and Cincinnati exceeded the absolute value of resistance. However, the social interaction levels of these cities are still lower than those in pre-pandemic situations (Table 1). This can be attributed to the restriction and changes in social connectedness resulting from the prolonged implementation of social distancing measures. Overall, the obtained resistance and recovery indicators provide a

Table 1
The calculated resistance and recovery indicators in investigated MSAs.

MSA	Resistance in the first response	Recovery in the first response	Resistance in the second response	Recovery in the second response
Atlanta	−5.44	1.77	−0.41	0.71
Austin	−5.29	1.63	−1.00	1.15
Baltimore	−5.96	1.96	−0.87	0.92
Boston	−6.34	1.88	−0.84	0.74
Charlotte	−4.80	2.01	−0.60	0.97
Chicago	−5.32	1.95	−0.76	0.83
Cincinnati	−4.16	2.17	−0.86	1.03
Dallas	−7.15	2.57	−1.23	1.47
Denver	−5.85	2.42	−0.53	0.62
Detroit	−6.57	2.85	−0.75	0.71
Houston	−6.26	2.10	−0.83	1.08
Las Vegas	−7.88	2.65	−0.57	1.05
Los Angeles	−7.26	1.37	−0.54	0.63
Miami	−5.19	1.48	−0.08	0.33
Minneapolis	−4.13	1.83	−0.65	0.64
New York	−6.99	1.98	−0.90	0.78
Orlando	−4.31	1.64	−0.33	0.44
Philadelphia	−6.83	2.17	−1.05	1.00
Phoenix	−5.44	1.54	−0.41	1.03
Pittsburgh	−5.07	2.36	−0.86	1.01
Portland	−7.52	2.44	−1.12	1.26
Riverside	−7.90	2.28	−0.66	1.02
Sacramento	−7.28	2.24	−0.55	0.84
San Antonio	−5.89	1.99	−1.18	1.53
San Diego	−8.01	2.27	−0.69	0.84
San Francisco	−7.25	1.33	−0.50	0.51
Seattle	−6.00	1.97	−0.77	0.85
St. Louis	−5.01	2.27	−0.75	1.15
Tampa	−3.56	1.52	−0.25	0.45
Washington D.C.	−5.55	1.33	−0.66	0.62

quantitative means to assess the degree of loss or recovery of social networks.

To examine the resistance and recovery of social networks, we employed Pearson correlation to test the correlation between resistance and recovery for all thirty MSAs. The correlation between resistance and recovery is significant at the significance level of 0.05 (Fig. 4), indicating a weak negative correction. This suggests that MSAs with lower resistance tend to have greater recovery. This pattern is logical, as regions with lower resistance (greater damage to network average degree per unit of time) are typically more responsive to policies and social activities. As restrictive policies begin to ease, MSAs with high sensitivity can proactively adapt to policies and rebuild and enhance social connectedness.

Resistance and recovery indicators were employed to further assess the resilience of the thirty chosen MSAs. The resilience indicator proposes that urban resilience in MSAs may be correlated with socioeconomic factors. MSAs with high population density and intense economic activities are at greater risk of COVID-19 transmission, resulting in a low rank in resilience for the New York (large, dense urban superstars), Los Angeles, San Francisco, Washington D.C. (early outbreak centers), and Miami (severe outbreak centers) (see Fig. 5). It is plausible that strict control measures may have been implemented in these MSAs with high economic development, leading to substantial damage to social connectedness. Lower urban resilience may also be associated with working patterns within MSAs. In developed MSAs, the work mode is relatively more diversified, allowing citizens to choose to work from home to avoid social contact, which also contributes to a slower recovery of social connectedness.

4.3. Spatiotemporal evolution patterns of social network centrality

The distribution of social network centrality in different periods displays a stratified pattern. Specifically, during periods of no control, strict control, and less control, the degree centrality of the core region in each MSA initially decreased and then increased (see Fig. 6), consistent with the change in the structural characteristics of social networks. Throughout the COVID-19 pandemic, the implementation of social distancing policies, such as shelter-in-place orders, stay-at-home orders, and bans on gatherings of certain sizes, effectively reduced interactions in society to slow the spread of COVID-19. Nevertheless, the need for economic development compelled a gradual loosening of restrictive policies, resulting in a gradual recovery of social connectedness in core regions.

We observe that the COVID-19 pandemic has affected the spatial structure of all selected MSAs (see Fig. 7). Table 2 provides specific evolution patterns for each MSA. The spatial structure of urban core nodes primarily follows the "expand-shrink" evolution process (Fig. 7). During the period of strict control, Atlanta, Boston, and Chicago displayed upward-shifted peaks, indicating a greater distance from the center of gravity compared to the non-strictly controlled period, which suggests the core regions in these MSAs expanded. However, from the strict period to the less strict period, the peak values in these MSAs presented a downward-shifted pattern with decreased peak distance, indicating a shrinking of the core region's structure. Fig. S3 in the Supplementary Materials presents the evolution dynamics of Atlanta MSA. The dynamic mechanism of changes in core regions may be due to policy constraints (Dubois & Dimanche, 2022). For instance, Las Vegas, a well-known tourist and entertainment MSA, experienced reduced non-essential visits to entertainment venues and theme parks due to the social distancing policies implemented during the severe COVID-19 situation. As non-essential travel typically covers short distances, social connectedness became unconcentrated. Later, during a less restricted period when non-essential travel was permissible, human activities became dense and concentrated, as evidenced by the increased network degree centrality.

The evolution patterns of the central structure in the investigated MSAs exhibit considerable variation (Table 2). MSAs like Boston and Los Angeles present an expanding pattern, whereas MSAs like New York and Chicago present a "shrink–expand" pattern. In comparison, the evolution pattern of San Francisco is characterized by "shrink–shrink". The development of distinct evolutionary patterns in spatial structures within these MSAs could be linked to multiple factors, including land use, transportation networks, and sociodemographic attributes. Determining the specific contributions of factors that may cause disparities in the assessment patterns of network centrality exceeds the boundaries of this research. Nevertheless, we advocate for future endeavors to explore this subject further.

5. Discussion

Examining short- and long-term fluctuations in social networks can yield valuable insights for post-pandemic strategizing. In this research, we leveraged fine-grained mobile device data to evaluate the resilience and recuperation of thirty selected Metropolitan Statistical Areas

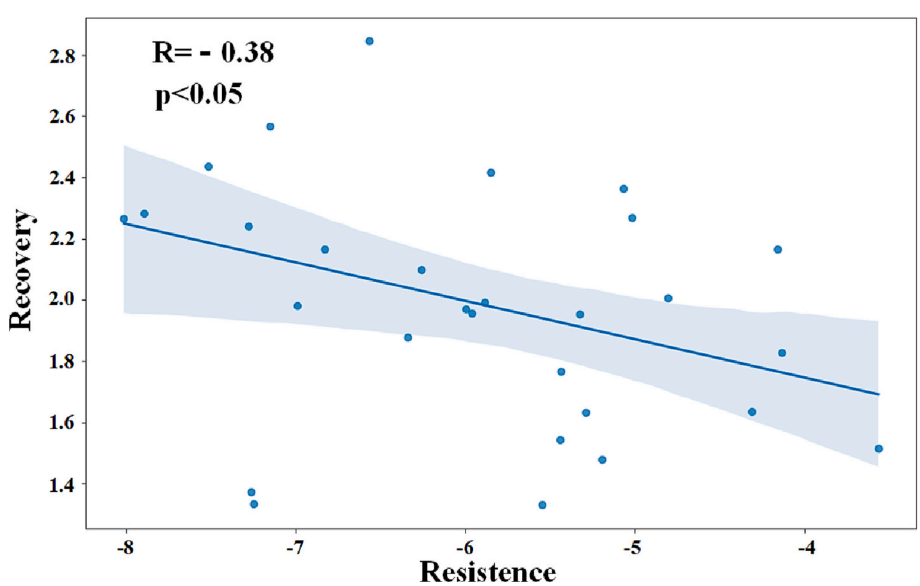

Fig. 4. Social network resistance and recovery in the first response. The x-axis represents the resistance indicator, and the y-axis represents the recovery indicator.

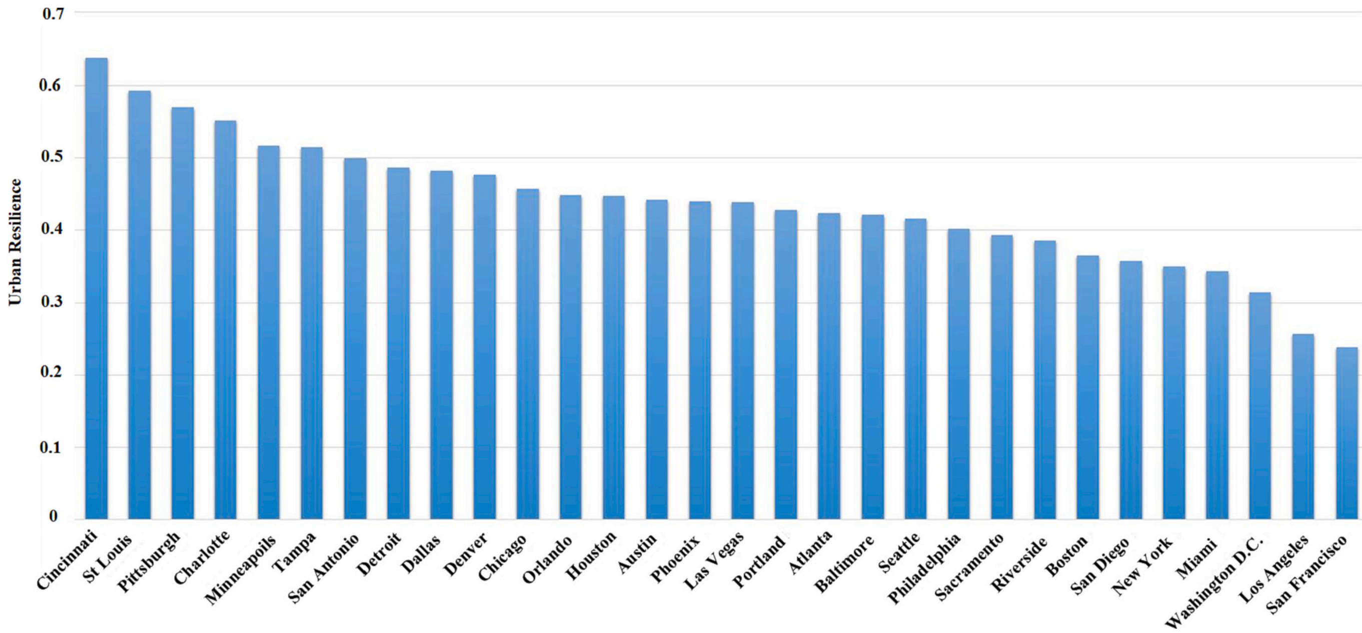

Fig. 5. Urban resilience assessment for thirty selected MSAs. The y-axis represents urban resilience, indicating the ratio of the absolute values of recovery and resistance.

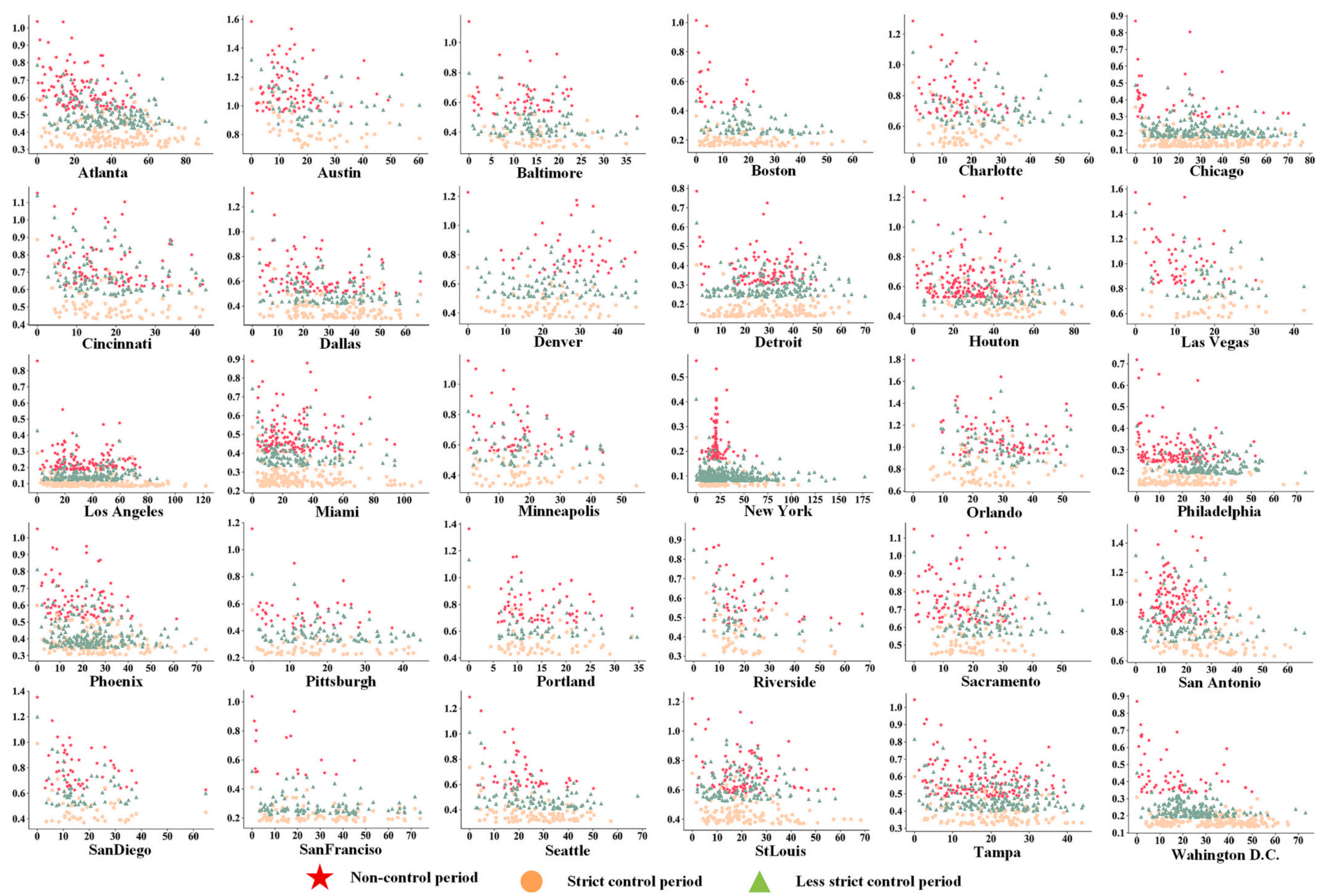

Fig. 6. The evolution characteristics of network centrality in different periods. The x-axis represents the center distance, while the y-axis represents the value of network centrality.

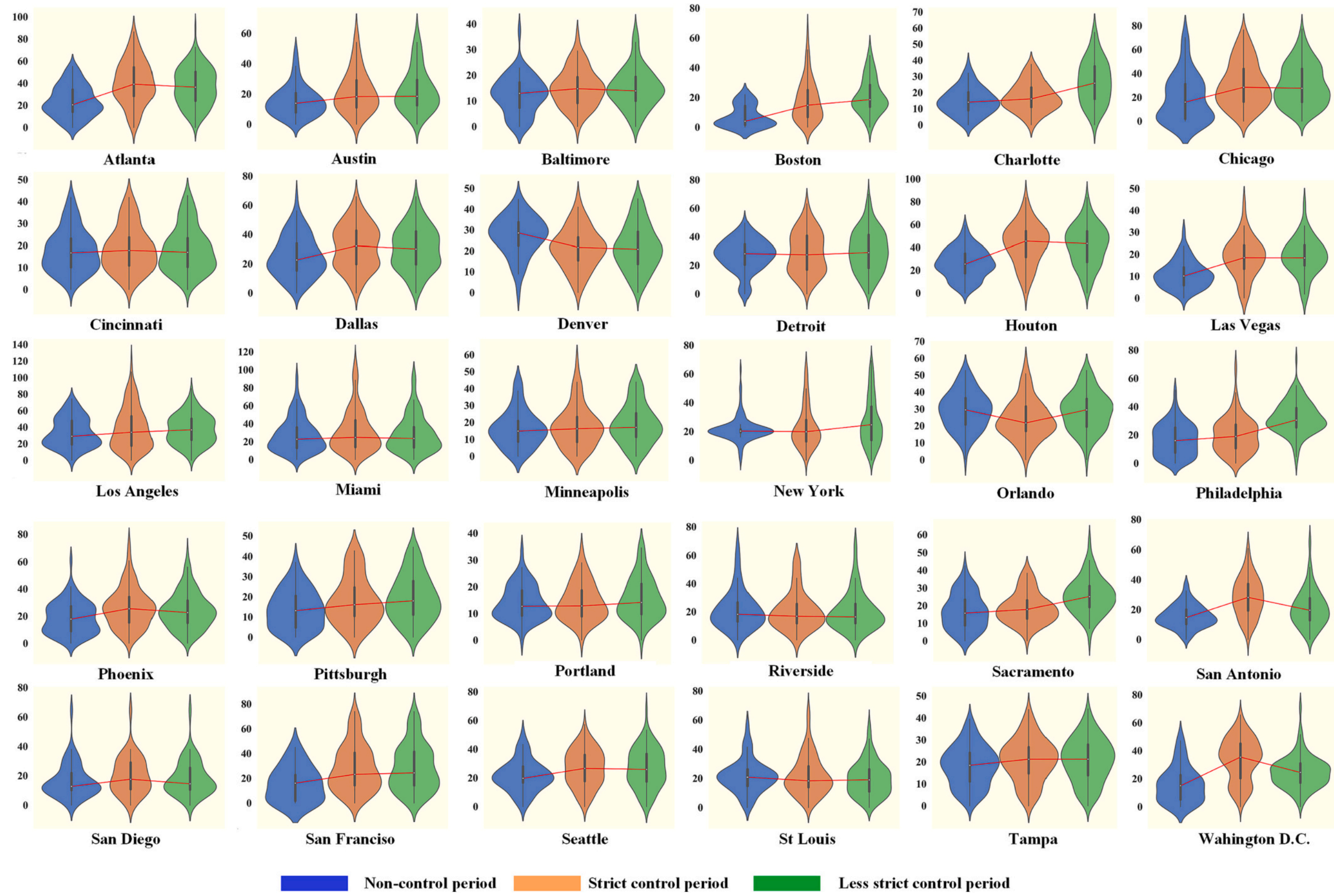

Fig. 7. Distance distribution of core regions in social networks in different periods. The red dashed line connects the median spatial distribution distance of the core area in different periods. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 2
The four distinct evolution patterns of central spatial structure observed in each MSA.

Evolution patterns	MSAs
Expand–shrink	Atlanta, Baltimore, Cincinnati, Dallas, Houston, Las Vegas, Miami, Phoenix, San Antonio, San Diego, Seattle, Tampa, Washington D.C.
Expand–expand	Boston, Charlotte, Los Angeles, Minneapolis, Pittsburgh, Riverside
Shrink–expand	Chicago, Detroit, New York, Orlando, Portland, Sacramento, St Louis
Shrink–shrink	Austin, Denver, Philadelphia, San Francisco

(MSAs) in the United States. Our observations indicate that although the overall trends in the structural features of social networks within each MSA during the COVID-19 pandemic exhibit similarities, the extent and pace of these changes, as well as the levels of recovery, differ across MSAs. The enforcement of restrictive measures resulted in the formation of sparse networks, whereas the relaxation of such policies contributed to the emergence of denser networks.

By employing social networks derived from mobile phone records, the urban resilience evaluation system devised in this study possesses the potential to precisely determine the ability of urban areas to withstand and recover from disruptive occurrences. Notably, urban recovery rates are found to be lower than urban resistance rates during the initial response to policy implementation, underscoring the challenge in restoring interaction levels to those observed prior to the pandemic. Moreover, during the second response phase to such policies, social connectedness experiences less disruption, emphasizing an enhanced capacity for adaptation to abrupt crises. The statistical analysis exploring the relationship between the extent of loss and recovery reveals a significant correlation, which mirrors the consistency in the efficiency of an MSA's response to policy measures throughout both the resistance and recovery phases. Our study's outcomes are congruent with the findings of prior research, such as Zhang et al. (2023), which examined the impact of COVID-19 and associated events on asset markets. Developed markets exhibited a more rapid response and recovery in relation to the COVID-19 pandemic as compared to emerging markets. The observed negative correlation between resistance and recovery further substantiates the efficacy of the proposed evaluation framework.

Each MSA displays unique resilience levels, which may be ascribed to the divergent social distancing policies enacted during the COVID-19 pandemic, as well as the heterogeneity in responses to such directives. When contrasting Tampa and Orlando with New York and Washington D.C., the latter pair experienced more substantial disruption, implying the execution of more stringent prevention and control measures. Conversely, MSAs like Dallas and Las Vegas exhibited enhanced resistance and recovery in comparison to New York, which is indicative of their social connectedness and capacity to actively adapt to policies with greater resilience. Public emergencies invariably disturb social connectedness and influence the spatial configuration of cities. The changing trajectory of central spatial structures is a direct consequence of the implementation of social distancing policies. Rigorous enforcement of these policies results in the decentralization of spatial arrangements. During the COVID-19 pandemic, the spatial structures of urban core locations initially expanded and later contracted. Network centrality presents diverse evolutionary patterns due to the innate disparities among MSAs. Based on our observations, we contend that the urban frameworks within certain MSAs have undergone alterations, thus necessitating the development of refined planning strategies to accommodate potential enduring changes in urban structures, as evidenced by human mobility data.

Finally, it is essential to recognize the limitations of this study. Firstly, we examined the changing trends of social networks through a piecewise linear fitting. However, the dynamics of social network structure characteristics are intricate and can be readily influenced by external factors, such as the enforcement of prevention and control measures, the introduction of economic revitalization policies, vaccine approvals, and events like the US presidential election (Yang et al., 2022). These elements can introduce complexity to network dynamics, resulting in non-linear shifts in social connectedness. Secondly, we investigated the evolution mode of social network structures by identifying the transition dates of social network changes within each MSA. Nevertheless, due to the distinct nature of MSAs (Bian et al., 2021), these transition dates may differ. In future endeavors, we aim to incorporate Bayesian online changepoint detection to pinpoint specific transition dates, enabling us to uncover more nuanced and significant evolution patterns of urban spatial structures. Moreover, a comprehensive evaluation of urban resilience can be conducted based on particular functional attributes, which would facilitate a deeper understanding of the driving mechanisms behind spatial structure evolution. Assessing changes in urban resilience under varying scenarios is also vital, as it can provide foundational knowledge for devising more effective policies.

6. Conclusion

The concept of resilience has gained significant importance as a vital approach to understanding the intricacies of social systems and their adaptability to the COVID-19 pandemic. In this research, we scrutinized the response of social interaction to social distancing policies by constructing intricate networks derived from human mobility data across the thirty most populous U.S. metropolitan statistical areas (MSAs). Moreover, we devised a resilience theory to evaluate urban resilience throughout the COVID-19 pandemic and to delve into the attributes of urban resilience. Furthermore, we investigated the distribution of centers and the progression patterns of central structures utilizing network centrality metrics. Our findings disclose a diverse array of social connectedness responses to social distancing policies, as well as heterogeneous social reactions across the examined MSAs. Generally, social networks appear to shift from dense to sparse configurations during restrictive orders, reverting from sparse to dense once restrictions are eased but ultimately remaining below pre-pandemic levels. Additionally, we identified alterations in social connectedness as demonstrated by network centrality, which can likely be attributed to the severity of policies and the inherent qualities of the MSAs under investigation. This study's outcomes are anticipated to aid governmental authorities in monitoring the evolving trends of the pandemic and other disruptive events. Moreover, our findings offer valuable scientific insights that can be used to bolster post-pandemic recovery and development efforts. By better understanding the dynamics of social connectedness and resilience during crises, policymakers can make more informed decisions to help communities thrive in the face of future challenges.

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CRediT authorship contribution statement

Yao Yao: Conceptualization, Methodology, Funding acquisition. **Zijin Guo:** Conceptualization, Formal analysis, Writing – original draft, Writing – review & editing. **Xiao Huang:** Conceptualization, Writing – original draft, Writing – review & editing, Data curation. **Shuliang Ren:** Methodology, Writing – review & editing. **Ying Hu:** Conceptualization, Methodology, Writing – review & editing. **Anning Dong:** Conceptualization, Writing – review & editing. **Qingfeng Guan:** Conceptualization, Resources, Writing – review & editing.

Declaration of competing interest

The authors claim no conflict of interest.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cities.2023.104361.

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