Quantifying Mobility Perturbation in America's Cities during COVID-19: A Network-Based Approach

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ABSTRACT

The pandemic of COVID-19 has caused severe disruptions in urban lives. Understanding and quantifying these disruptions is important to inform the development of targeted and effective measures to control the pandemic and its impact. One way of achieving this object is to measure the urban mobility perturbation caused by the pandemic. In this study, we built mobility-based networks for seven major metropolitan statistical areas (MSAs) across the United States in the years of 2019 and 2020, respectively. We quantified the disruptions of urban mobility by computing and comparing a set of network-based metrics before and during the pandemic. The proposed approach is able to uncover the impact of COVID-19 in cities and provides new insights into the resilience of cities when facing large-scale disasters.

INTRODUCTION

The world is currently facing a global public health crisis due to the COVID-19 pandemic, which has caused devastating life and economic losses (Chakraborty and Maity 2020). Epidemic control is gaining increasing attention from academia to mitigate the ongoing COVID-19 pandemic and better prepare us for future epidemics. Nonpharmaceutical Interventions (NPIs) (Yabe et al. 2020), particularly mobility tracking technologies and individuals' digital traces, are being used to help slow the spread of SARS-CoV-2.

Based on various digital data sources, such as vehicle GPS records, geo-tagged social media posts and location-based services, recent studies have shown that urban mobility changes under the impact of the COVID-19 pandemic. Various studies have demonstrated the overall trend of mobility reduction, and highlighted the impact of various self-isolation and social distancing measures (Huang et al. 2020; Schlosser et al. 2020). In addition, mathematical models and machine-learning models have been formulated to predict the spread of the pandemic or demonstrate the relationship between mobility and pandemic transmission (Brown et al. 2021; So et al. 2021). These studies have greatly advanced existing knowledge about the relationship of human mobility and pandemic spread.

Complex networks provide a powerful tool for analyzing human mobility. Human mobility can be structured as complex networks by taking areas as nodes and traffic flows between origins and destinations as links (Wang and Taylor, 2014). This complex network approach has been used in tracking perturbed mobility induced by the pandemic (Schlosser et al. 2020), revealing the relationship of the mobility network and the spread of pandemic (Freitas et al. 2020; Jia et al.

2020; So et al. 2021) and informing the modeling of pandemic spread based on mobility information (Brown et al. 2021; Mo et al. 2021).

However, existing studies that examine human mobility from the complex network perspective bear several notable limitations. Most studies focus on global metrics to describe mobility reduction and structural changes of the whole mobility networks (Armstrong et al. 2020; Schlosser et al. 2020), while few studies have looked into local metrics which deal with the relation of an individual node to the network structure and influence of this node on its neighbors. Local information provided by local metrics was found to have significant correlation with number and distribution of confirmed COVID-19 cases (Freitas et al. 2020), which is vital for predicting the pandemic spread within cities. In addition, few studies have compared the above network metrics and their COVID-19-induced perturbations across different cities. Such comparisons would provide further insights about how well the cities are dealing with the current pandemic.

This study aims to address the above limitations, by investigating global and local changes of mobility networks under the impact of COVID-19 in seven metropolitan statistical areas (MSAs) in the United States. Global and local metrics originated from network theory are used to study changes in mobility network properties in two different viewpoints (Freitas et al. 2020). Our study provides new insights for understanding and supporting intra-cities mobility interventions regarding the COVID-19 and other epidemics.

DATA AND ANALYSIS

Dataset. This study employs an anonymized mobility dataset from SafeGraph (2020) that measures travel flows within the United States at the Census block group (CBG) level in 2019 and 2020. Based on daily traces of around 20 million mobile devices in the country, the dataset provides information on (1) the population, i.e. the numbers of individuals living in a CBG; and (2) the trip volumes, i.e. the numbers of individuals who travel to other destination CBGs. Prior studies that used SafeGraph data to model the spread of COVID-19 have found that the data are generally representative of the U.S. population (Glaeser et al. 2020; Kang et al. 2020).

Table 1. Summary of basic information of the seven studied MSAs

	Atlanta	Boston	Houston	Los Angeles	Miami	New York	Washington
Population in 2019 (million)*	6.02	4.87	7.07	13.21	6.17	19.22	6.28
Area (km^2)*	22,486	9,033	21,395	12,559	13,145	17,315	17,009
Number of CBGs	2,597	3,416	3,019	8,245	3,417	14,323	3,517

*Source: https://www.citypopulation.de/en/usa/metro/

Seven MSAs, selected based on their diverse geographical distributions, are examined in this study. Basic information of these MSAs is summarized in Table 1. To construct the mobility networks for the years of 2019 and 2020, daily mobility flow data from Monday through Thursday in the second week of March, June, September and December were extracted from the SafeGraph data for each year (for March 2020, the flow data of the third week of the month were used, after the March 13 declaration of COVID-19 national emergency). The data were selected based on a 3-month interval to avoid seasonal variance in mobility flows and reduce the computational load while ensuring reliable results.

Network construction. Mobility networks G = (N, L, W) were constructed based on flow data of 16 weekdays in 2019 and 2020, respectively, where CBGs are nodes (N) and the trip volumes are weights (W) of the links (L). As such, we constructed mobility-based geosocial networks formed by urban physical activities rather than actual travel networks (Zhong et al. 2014).

Global metrics. We considered a variety of network metrics to describe the global properties of mobility networks and the underlying urban spatial structures (see Table 2).

Table 2. Definitions of global metrics

Metric	Definition	References
Number of edges	The total number of links in a network.	(Zhong et al. 2014)
Average shortest path length	The average value of the minimum network distance (number of edges) between each two nodes in a network.	(Schlosser et al. 2020)
Average trip flow	The average trip volume of all links in a network.	(Freitas et al. 2020)
Density	The ratio between the total number of links and the maximum number of possible links in a network.	(D'Agata et al. 2013)
Clustering coefficient	The fraction of number of closed triplets (or 3 x triangles) in the total number of triplets (both open and closed) in a network.	(Fiore and Härri 2008)

Local metrics. Four local metrics were used to study the degree of importance of each node in the network and its influence on other nodes. These metrics include:

Table 3. Definitions of local metrics

Metric	Definition	Reference
Degree	The number of links directly connected to the node.	(So et al. 2021)
Strength	The accumulated flow from adjacent nodes.	(Zhong et al. 2014)
Local clustering coefficient	The proportion of links between the nodes within its neighborhood divided by the number of links that could possibly exist between them.	(Schlosser et al. 2020)
Closeness centrality	The mean geodesic distance (i.e., the shortest path) between a node and all other nodes reachable from it.	(D'Agata et al. 2013)

RESULTS AND ANALYSIS

An overview of the impact of pandemic. Figure 1 shows the change rates of all global measures in 2020, compared to the previous year, in the seven MSAs. The number of edges decreased in all MSAs, indicating the connectivities between different CBGs were reduced. The average trip volume also decreased, reflecting a reduced travel demand. In contrast, the length of shortest paths increased slightly, indicating that travel costs between distant areas may have increased. We also found decreases in density and global cluster coefficient in the mobility network in 2020. These changes indicated that the mobility network became sparser and formed fewer clusters under the influence of the pandemic.

There were substantial differences between the MSAs in the extent of perturbation, especially in terms of the number of edges, the average shortest path length, and density. The results revealed that mobility in New York, Boston, Los Angeles, and Washington were more affected than mobility in Atlanta, Houston, and Miami. Notably, the numbers of edges and density in New York, Boston, Los Angeles and Washington were reduced by over 50%.

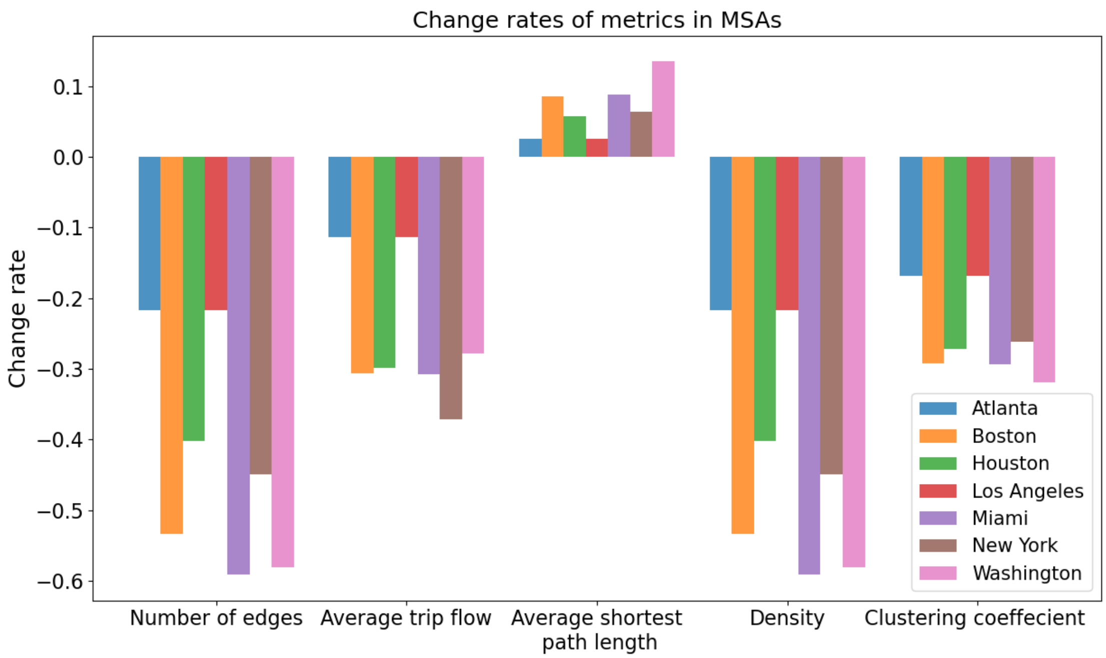

Figure 1. Change rates of basic network metrics from 2019 to 2020

Our results showed notable trends of decreasing mobility under the impact of COVID-19 in various metropolitan areas, which align with findings reported in previous studies (Abu-Rayash and Dincer 2020; Armstrong et al. 2020).Such changes can be largely attributed to self-isolation, lockdowns and other social distancing measures. Also, although all seven MSAs have become less connected in 2020, there is a significant difference between the seven metropolitan areas. Overall, MSAs of New York, Boston, Los Angeles and Washington witnessed larger perturbations than the MSAs of Atlanta, Houston, and Miami. Such observations are generally consistent with prior research (Armstrong et al. 2020; Ruiz-Euler et al. 2020). The different extents of perturbation are possibly tied to the differences of the infection and hospitalization rates in these MSAs as well as their local pandemic control policies and enforcement.

Local centrality under the impact of pandemic. In our next set of analyses, local metrics were used to study changes of local properties in mobility networks. The degree and strength of the nodes were plotted for the seven MSAs in Figure 2, which can depict the distribution of density and intensity of connections in mobility networks (Zhong et al. 2014). As shown in the figure, the number of nodes with high and intense connections to other nodes decreased in the mobility networks in 2020. There was a sharp decline in the number of nodes with high degree and intensive strength in the MSAs of Boston, Houston, New York, Los Angeles, Miami and Washington, which was not observed in the Atlanta MSA.

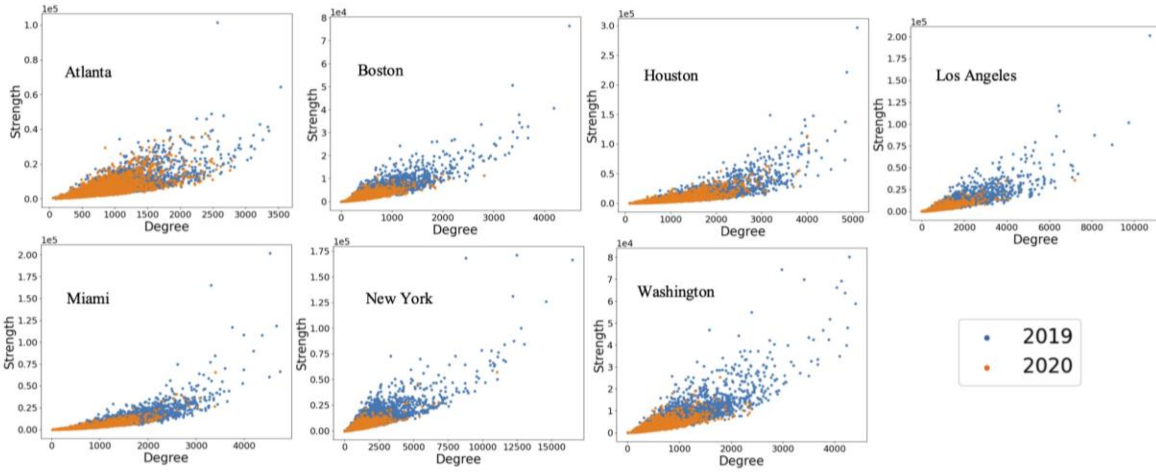

Figure 2. Node degree and strength distributions in mobility networks in 2019 and 2020

In addition, the local clustering coefficient was calculated for each CBG in each MSA network to explore the concentration and dispersion of mobility network structures. Figure 3 shows the local clustering coefficients decreased in all MSAs. Consistent with the results about global clustering coefficients shown in Figure 1, apart from the Atlanta MSA which was affected lightly, the magnitude of impact on local clustering, reflected by the changes in distributions of local clustering coefficient, did not show a significant difference among other MSAs.

The affected distributions of node degree and strength in 2020 suggested that individuals had fewer destination choices and reduced their visitation frequencies. Moreover, the decrease in local clustering coefficients indicated a declining tendency for individuals to hold social gatherings. Together with the increased length of the shortest paths in mobility networks, our results indicated a reduction of the "small world" phenomenon (Schlosser et al. 2020; Zhong et al. 2014), i.e., highly clustered networks with small length of average shortest path. As prior research pointed out, such reduction of the "small world" phenomenon might slow down the spread of the pandemic (Schlosser et al. 2020; So et al. 2021).

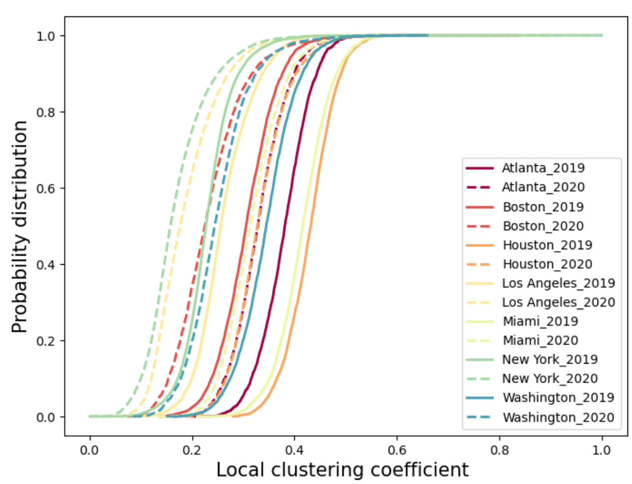

Figure 3. Local clustering distributions in all MSAs in 2019 and 2020.

It is noteworthy that the overall mobility reduction is not always consistent with the magnitude of changes in mobility network properties when comparing results in Figures 1 and 3. The inconsistency might be caused by robustness and tolerance in mobility networks. Several properties, such as clustering coefficient, in mobility networks are less sensitive to perturbations compared with mobility reduction because of the inherent capability of mobility networks to cope with failures and perturbations.

Additionally, Figure 4 shows that the number of nodes with lower closeness centrality increased while the ones with higher closeness centrality decreased in the mobility networks in 2020. The distributions of closeness centrality of all MSAs showed an overall trend of reduction in 2020 compared to the previous year (dotted lines vs. solid lines).

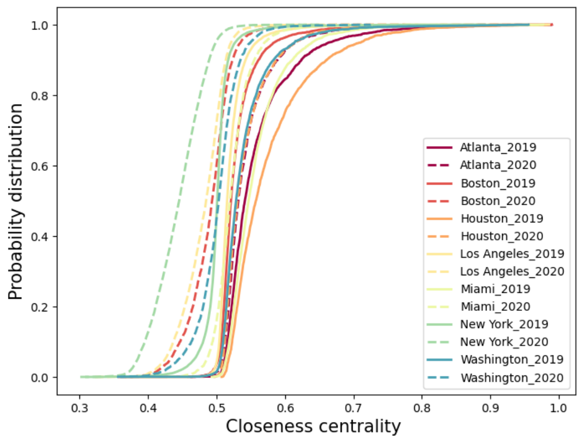

Figure 4. Comparisons of closeness centrality distributions in 2019 and 2020.

In summary, the seven MSAs showed two different types of response patterns: (1) we observe that the MSAs of Atlanta, Houston and Miami were less affected by the COVID-19. Although the number of areas with higher closeness centrality decreased, the overall level, especially the minimum level of closeness centrality, was similar in 2019 and 2020; (2) in contrast, the MSAs of New York, Boston, Los Angeles and Washington experienced a more severe perturbation. There was a more substantial decline of closeness centrality besides the decreasing numbers of areas with higher closeness centrality. The results indicated mobility networks in seven MSAs became less convenient and efficient under the impact of the pandemic, especially for the MSAs of New York, Boston, Los Angeles and Washington.

CONCLUSIONS

In this study, we constructed mobility networks in seven MSAs in the United States. To capture the mobility perturbation caused by the COVID-19, we computed and compared a set of global and local network metrics. Global metrics describe the properties of the whole network, while local metrics provide details about the relation of specific nodes to the network structure. Structures of mobility networks can be comprehensively characterized based on these local and global metrics. The results demonstrated that (1) there was a considerable reduction of mobility during the pandemic, and (2) MSAs showed different response patterns, with MSAs of New York, Boston, Los Angeles and Washington D.C experiencing a higher level of disruptions.

We acknowledge a few limitations in this study which we aim to address in future research. We only quantified the differences in affected spatial structures of MSAs and yet the causes of these differences should be further explored. In addition, future research should be done to explore how the findings from this study could be transformed into improved contagion transmission simulations and modeling and actionable pandemic control measures. The deep understanding of the relationship between human mobility and the transmission of deadly diseases will provide essential support to policymakers in making more effective pandemic response and relief plans and, hence, improve the resilience of cities against future pandemic risks.

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