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Examining human mobility changes during COVID-19 across socioeconomic groups: a comparative analysis of San Diego County and New York City

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Abstract

The COVID-19 pandemic brought unprecedented changes to various aspects of daily life, profoundly affecting human mobility. These changes in mobility patterns were not uniform, as numerous factors, including public health measures, socioeconomic status, and urban infrastructure, influenced them. This study examines human mobility changes during COVID-19 in San Diego County and New York City, employing Latent Profile Analysis (LPA) and various network measures to analyze connectivity and socioeconomic status (SES) within these regions. While many COVID-19 and mobility studies have revealed overall reductions in mobility or changes in mobility patterns, they often fail to specify 'where' these changes occur and lack a detailed understanding of the relationship between SES and mobility changes. This creates a significant research gap in understanding the spatial and socioeconomic dimensions of mobility changes during the pandemic. This study aims to address this gap by providing a comprehensive analysis of how mobility patterns varied across different socioeconomic groups during the pandemic. By comparing mobility patterns before and during the pandemic, we aim to shed light on how this unprecedented event impacted different communities. Our research contributes to the literature by employing network science to examine COVID-19's impact on human mobility, integrating SES variables into the analysis of mobility networks. This approach provides a detailed understanding of how social and economic factors influence movement patterns and urban connectivity, highlighting disparities in mobility and access across different socioeconomic groups. The results identify areas functioning as hubs or bridges and illustrate how these roles changed during COVID-19, revealing existing societal inequalities. Specifically, we observed that urban parks and rural areas with national parks became significant mobility hubs during the pandemic, while affluent areas with high educational attainment saw a decline in centrality measures, indicating a shift in urban mobility dynamics and exacerbating pre-existing socioeconomic disparities.

Keywords Urban mobility, Urban spatial structure, Networks, COVID-19

1 Introduction

On January 30, 2020, the World Health Organization (WHO) declared the COVID-19 outbreak a 'Public Health Emergency of International Concern,' and on March 11, 2020, it was officially classified as a pandemic (WHO, 2020). This global health crisis significantly impacted people's mobility choices, bringing unprecedented changes to various aspects of daily life and profoundly affecting human mobility. Lockdowns, social

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distancing measures, and remote work policies drastically altered daily routines, leading to significant shifts in how and where people moved. These changes in mobility patterns were not uniform; they varied widely depending on a range of factors, including public health measures implemented by local authorities, socioeconomic status, and the existing urban infrastructure (Weill et al., 2020; Gao et al., 2020).

Public health measures such as lockdowns and travel restrictions were implemented to curb the spread of the virus, resulting in a marked decrease in overall mobility (Gao et al., 2020). However, these measures did not affect all populations equally. The pandemic has brought the issue of urban inequality into sharp focus, disproportionately affecting disadvantaged communities and exposing deep-rooted inequalities in many cities (Cordes and Castro, 2020; Maroko et al., 2020; Sampson and Levy, 2020; Duenas et al., 2021; Marlow et al., 2021; Levy et al., 2022). Moreover, responses to social distancing differed by income (Weill et al., 2020). People in higher socioeconomic groups often had the flexibility to work from home and access resources with minimal movement. In comparison, those in lower socioeconomic groups, who were more likely to be service workers needing to work face-to-face, continued to commute and travel, exposing them to more significant risks (Weill et al., 2020). Urban infrastructure also played a critical role in shaping mobility patterns during the pandemic. Cities with well-developed public transportation systems experienced different mobility shifts than those reliant on private vehicles (Glaeser et al., 2022). Additionally, the density and layout of urban areas influenced how people moved within the city, with some areas seeing more significant reductions in mobility due to their dependence on public transit and others remaining relatively unchanged (Sharifi and Khavarian-Garmsir, 2020).

Recent advancements in geospatial data, such as mobile phone records, GPS traces, and social media posts, have opened up new possibilities for studying human mobility (Gao et al., 2013; Prestby et al., 2020; Wang et al., 2022a; Nilforoshan et al., 2023). These data sources provide detailed information on the daily movements of individuals, allowing researchers to analyze the connectivity between different parts of a city and reveal the underlying spatial and social networks (Bennett and Haining, 1985; Batty, 2009).

While numerous studies have documented overall reductions in mobility or shifts in movement patterns during the pandemic, many have not pinpointed the locations where these changes occurred, nor have they thoroughly explored the relationship between SES and mobility changes. This lack of detailed spatial and socioeconomic analysis has created a substantial research gap, limiting our understanding of how mobility shifts during the pandemic varied across different communities and urban landscapes. To address this gap, our study aims to provide a detailed analysis of how mobility patterns differed among various socioeconomic groups during the pandemic. By comparing mobility patterns from mobile phone data from before and during the pandemic, we seek to reveal how this unprecedented global event affected different population segments. Our research enhances existing knowledge by integrating SES variables into mobility network analysis, which allows for a more comprehensive understanding of the interaction between physical movement and social factors. The findings highlight specific areas that served as mobility hubs or bridges and illustrate how these roles evolved during COVID-19, thereby exposing underlying societal inequalities and disparities. The main research questions guiding this study are as follows:

- What are the human mobility networks and hubs identified through mobile phone data in San Diego County and New York City?
- How do they relate to the spatial patterns of socioeconomic status within a city?
- How did the COVID-19 pandemic affect these mobility patterns?

By addressing these questions, we aim to enhance our understanding of urban mobility dynamics and provide valuable insights for planners and policymakers striving to create more equitable and inclusive cities.

The remainder of this paper is organized as follows. The next section reviews the literature on mobility changes during the COVID-19 pandemic from a network science perspective, focusing on studies that utilize different data sources. Section 3 outlines the study areas and data sources, while Section 4 details the methods employed in this research. Section 5 presents the key findings from our analyses. In Section 6, we discuss these findings, explore implications for urban planning and policy, address limitations, and offer suggestions for future research.

2 Related work

The COVID-19 pandemic profoundly impacted human mobility, leading to significant reductions in movement, increased localized activities, notable migration trends from urban to rural areas, and disruptions in social connectedness. These changes have been studied using diverse data sources, such as mobile phone data, social media, census, and migration records, employing a network science perspective to provide in-depth insights into mobility patterns and urban resilience.

Lockdown measures in various regions led to marked reductions in mobility and shifts in localized movements. For instance, Rowe et al. (2023b) used mobile phone data from Meta-Facebook to construct mobility networks, revealing significant regional and socioeconomic variations in the UK. Similarly, cellular network data in Brazil highlighted shifts in traffic patterns from downtown areas to other locations, demonstrating variations in mobility across different socioeconomic groups (Ayan et al., 2021). Government-imposed restrictions, such as stay-at-home orders, social distancing guidelines, and the closure of nonessential businesses, aimed to reduce physical interactions and mitigate the virus's spread, leading to significant reductions in human mobility (Gao et al., 2020; Hadjidemetriou et al., 2020; Yabe et al., 2020; Noi et al., 2022). These measures effectively controlled the spread of COVID-19, especially in the early stages of the outbreak (Wang et al., 2020).

The pandemic also triggered notable urban-to-rural migration trends globally. In Latin America, mobile phone location data identified migration patterns driven by the search for safer living conditions and remote work opportunities (Rowe et al., 2023a). In the UK, Twitter data tracked real-time mobility trends, revealing increased migration from urban to rural areas and providing timely insights into the long-term impact of the pandemic on migration (Wang et al., 2022b). In Spain, administrative population register data identified significant migration to rural areas, with diverse demographics among migrants, including young adults, families, retirees, and foreign-born populations, particularly from Latin American countries (Gonzalez-Leonardo et al., 2022).

Urban resilience and social connectedness were key areas of study during the pandemic. Mobile phone data was used to create social networks, showing how these networks became sparser during lockdowns but gradually recovered, illustrating the critical role of network stability in urban resilience (Yao et al., 2023). Additionally, in Mexico City, mobile phone data revealed disparities in mobility reductions among different SES groups, emphasizing the exacerbation of existing socioeconomic disparities (Fontanelli et al., 2022). Vulnerable populations, including communities of color, low-income groups, older adults, children, and individuals with preexisting health conditions, were more severely impacted (Coleman et al., 2022; Sheikhattari et al., 2023). Counties with higher Asian populations saw the most significant reduction in mobility, while those with higher African American populations experienced the highest case-fatality ratios, with initial pronounced racial differences in human mobility (Hu et al., 2022).

The ability to stay at home during the pandemic highlighted existing disparities. While some individuals could work remotely, low-income workers, particularly those in service industries, had to work physically, revealing disparities in adherence to remote work practices (Hadjidemetriou et al., 2020). Higher-income regions exhibited greater reductions in mobility compared to lower-income regions, which showed less adherence to stay-at-home orders (Huang et al., 2022). The impact on transportation-related behaviors and human mobility patterns has been significant (Huang et al., 2020). Social determinants of health, including neighborhood environment, access to healthcare, education, and economic stability, influenced vulnerability to COVID-19, exacerbating existing disparities and inequities in vulnerable populations (Bhaskar et al., 2020; Sheikhattari et al., 2023).

Advanced network analysis techniques provided deeper insights into the pandemic's impact on global mobility. Graph embedding techniques, such as the node2vec algorithm, were employed to analyze global mobility networks from Meta's travel pattern data, highlighting the significance of high-page rank centrality countries in controlling infection spread and informing targeted interventions and resource allocation (Awasthi et al., 2023).

3 Study area and data

3.1 Study area

The study focuses on two representative metropolitan areas: San Diego County, CA, and New York City, NY. San Diego County and New York City have diverse populations with different demographic compositions. New York City has a larger proportion of Black residents (23.1%) compared to San Diego County (5.6%), while San Diego County has a higher proportion of Non-Hispanic White (43.4% vs. 31.2%) and Hispanic (35.0% vs. 29.0%) residents. Both areas have substantial Asian populations, with New York City having a slightly higher proportion (14.5%) than San Diego County (13.1%) (U.S. Census Bureau, 2019a). Furthermore, New York City is known for its high-density urban core and extensive public transportation system, which supports many pedestrian commuters and reduces reliance on private vehicles. In contrast, San Diego County has a more sprawling urban structure, encompassing both urban and rural areas, with a higher reliance on private vehicles (Ewing et al., 2016).

3.2 Census data

This study uses data from the 2015-2019 American Community Survey (ACS) 5-Year Estimates, which were retrieved via the U.S. Census Bureau's API using Python. The ACS is an ongoing survey that provides detailed information about the demographic, social, economic, and housing characteristics of the U.S. population (U.S. Census Bureau, 2020). The 5-year estimates are derived from data collected over a 60-month period, offering more reliable estimates for small geographic areas and population subgroups compared to the 1-year estimates (U.S. Census Bureau, 2018).

The socioeconomic variables included in this study are race, educational attainment, median household income, home ownership, and population under the poverty line. These variables provide a comprehensive overview of the social and economic conditions in the study areas. Each variable was chosen for its ability to capture critical aspects of socioeconomic status and their potential relationship to urban spatial patterns: race highlights demographic diversity and potential spatial segregation; educational attainment reflects access to and quality of education, which can vary spatially; median household income indicates economic well-being and can influence residential patterns; home ownership serves as a proxy for economic stability and investment in specific areas; and the population under the poverty line identifies the extent of economic deprivation, which can affect and be affected by spatial distribution within urban areas.

The spatial unit chosen for this study is the census tract. Census tracts are small, relatively permanent statistical subdivisions of a county, designed to be as homogeneous as possible with respect to population characteristics, economic status, and living conditions (U.S. Census Bureau, 2019b). Census tracts generally have a population size between 1,200 and 8,000 people, with an optimum size of 4,000 people (U.S. Census Bureau, 2019b). The geographic size of census tracts varies widely depending on the density of settlement. In urban areas, census tracts are often smaller and more compact, while in rural areas, they may be larger and more spatially dispersed.

3.3 Mobility data

This study utilizes SafeGraph's Social Distancing Metrics dataset from 2019 to 2020 to analyze human mobility patterns. SafeGraph is a company that aggregates anonymized location data from various applications to provide insights into human mobility patterns. The Social Distancing Metrics dataset is derived from a panel of GPS pings from anonymous mobile devices, which enables the observation of movement patterns at various geographic scales (SafeGraph, 2020). The dataset includes several metrics that quantify the level of social distancing and its impact on mobility. These metrics include aggregated daily counts of trips between home census block groups and destination block groups, the number of devices staying home, the median distance traveled from home, the proportion of devices leaving home in a day, and the average time spent away from home (SafeGraph, 2020). The data is aggregated at the census block group level, providing a high level of spatial granularity for analyzing mobility patterns. SafeGraph provided the Social Distancing Metrics dataset free of charge to researchers during the COVID-19 pandemic, and this mobility data has been widely used in studies investigating the impact of the pandemic on human mobility and social distancing practices (Gao et al., 2020; Marlow et al., 2021; Li et al., 2022). The large sample size and high spatiotemporal resolution of the data make it a valuable resource for understanding changes in mobility patterns over time and across different geographic areas.

4 Methodology

Figure 1 illustrates the flowchart for this study. Using Census data, we conduct a Latent Profile Analysis (LPA) to classify census tracts based on various socioeconomic variables. Utilizing human mobility data, we first construct a direct network where nodes represent census tracts and edges represent spatial interactions or trips between nodes. Subsequently, we calculate diverse network measures to examine urban spatial structure.

4.1 Node characteristics and Latent Profile Analysis (LPA)

In the constructed network model, which captures mobility patterns across different areas, the nodes represent census tracts, with edges indicating the presence of mobility flows or connections between those geographic units. Data from the ACS can enhance nodes in such networks, meaning each node represents not just a location but also the demographic and socioeconomic characteristics of that area. Classifying these nodes, considering all these variables in unison requires sophisticated methods. One particularly relevant classification method is LPA. LPA is a statistical approach used for identifying hidden or latent profiles or groups within a dataset. Although it is similar to Latent Class Analysis (LCA), which uses categorical latent variables, LPA can handle both continuous and categorical indicators. (Gibson, 1959). In the context of our study, particularly to examine mobility hubs and the spatial patterns of socioeconomic status, LPA is employed to cluster nodes (census tracts) that exhibit similar characteristics. The key advantage of LPA lies in its ability to classify census tracts based on a combination of several attributes, rather than just one. This multifaceted approach allows for a more comprehensive and representative classification of the census tracts. Moreover, we chose LPA due to its flexibility and robustness. LPA does not require pre-specifying the number of clusters, allowing the data to guide the determination of the number of profiles. Additionally, LPA provides fit indices that help in evaluating and selecting the optimal model. Upon comparing the results with those from multivariate

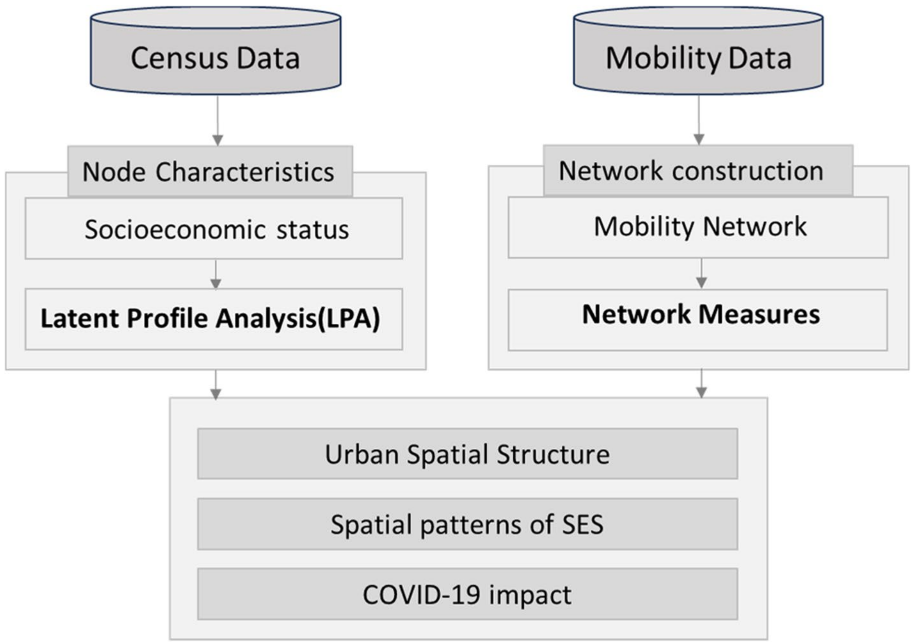

Fig. 1 The progression from data collection to analysis

clustering in ArcGIS Pro 3.2, LPA produced maps with more coherent and interpretable profiles. In this study, seven variables are used for LPA: race (Non-Hispanic White, Non-Hispanic Black, Hispanic), educational attainment (percentage of population with a bachelor's degree or higher), median household income, home ownership (owner), and the percentage of people living below the poverty line. For race/ethnic variables, we focus on three groups—White, Black, and Hispanic. These groups are selected due to their persistent segregation patterns, as documented in various studies (Reardon, 2016; Popescu et al., 2018; Fahle et al., 2020), which make them suitable for analyzing distinct socioeconomic and demographic characteristics. By incorporating race and diverse socioeconomic factors, LPA provides a nuanced understanding of the underlying profiles within the census tracts, enabling a more accurate and meaningful classification of these areas.

4.2 Network measures

In this study, we used a network science perspective to analyze mobility networks to understand how different parts of cities are utilized. Network science examines how nodes (vertices) and edges (connections between nodes) interact within a network to form patterns, reveal underlying structures, and influence system behavior. For comprehensive definitions and concepts, see Newman (2018). Key network measures used in our analysis include:

- Degree Centrality: Quantifies a node's number of direct connections, identifying key hubs within the network (Kitsak et al., 2010; Zhang and Luo, 2017). In directed graphs, this measure is split into in-degree and out-degree.
- Eigenvector Centrality: Considers both the quantity and quality of a node's connections, assessing its influence within the network (Newman, 2018).
- PageRank: Extends centrality measures by considering the direction and weight of connections and the entire network structure (Rogers, 2002), crucial for identifying critical nodes in human mobility networks.
- Closeness Centrality: Measures how close a node is to all other nodes in the network, indicating accessibility (Okamoto et al., 2008).
- Betweenness Centrality: Evaluates a node's role as a bridge connecting other important nodes, essential for understanding connectivity within the network (Freeman et al., 1991).
- Clustering Coefficient: Indicates the degree to which nodes' neighbors are interconnected, reflecting the network's local structure (Watts and Strogatz, 1998).

These measures collectively provide a comprehensive view of the network's structure and the roles of individual nodes within it. This study created a weighted directed graph and limited Origin-Destination (O-D) networks at the state level for California and New York.

Table 1 Summary statistics by class in San Diego County

Variable	Class 1	Class 2	Class 3	Class 4	Class 5
% White	84.47	64.62	92.62	76.75	72.13
% Black	3.76	7.00	0.59	2.48	8.15
% Hispanic	17.76	51.27	7.80	16.89	22.74
% BA or More	28.00	23.80	38.11	52.71	46.68
% Owner Occupied	48.48	46.95	88.48	63.38	22.34
% Below Poverty Level	15.39	15.18	7.94	6.61	19.61
Median Household Income	61826.5	62025.5	108913.0	101154.0	64734.0
Count	2	298	3	281	44

Table 2 Summary statistics by class in New York City

Variable	Class 1	Class 2	Class 3	Class 4	Class 5
% White	87.00	32.36	94.42	76.64	27.30
% Black	3.97	16.45	0.41	3.31	56.74
% Hispanic	8.51	45.75	5.61	12.44	17.61
% BA or More	30.90	25.69	41.39	64.17	33.20
% Owner Occupied	47.75	26.45	85.08	43.61	28.75
% Below Poverty Level	17.84	22.08	4.40	7.63	20.44
Median Household Income	59802.0	54868.0	97991.0	100667.5	60467.5
Count	36	969	18	502	642

Network measures were calculated monthly throughout 2019, averaged, and then compared to the network measures for April 2020. The Python library NetworkX was employed for these calculations.

5 Results

5.1 Unveiling urban typologies: LPA

Tables 1 and 2 present summary statistics by LPA classes for each variable for San Diego County and New York City, respectively.

By examining the proportions of each variable for each class, we labeled each class. The classification of the census tracts into five distinct classes based on demographic and SES variables is articulated as follows:

- Class 1 (Red): 'High Proportion White with Low SES.'
- Class 2 (Blue): 'High Proportion Hispanic with Low SES.'
- Class 3 (Green): 'High Proportion White with High SES - High Homeowners.'
- Class 4 (Purple): 'High Proportion White with High SES - High Education Attainment.'
- Class 5 (Orange): 'High Proportion Black with Low SES.'

The classification of SES into high and low was done using relative thresholds. This means that SES levels were determined based on the distribution of socioeconomic indicators within the dataset, rather than using fixed absolute values. These LPA classes provide a more comprehensive understanding of the racial and socioeconomic landscape in the cities studied. By considering the proportion of racial groups and the associated SES, the LPA analysis reveals the intersectionality of race and class in shaping urban spatial patterns. Figures 2 and 3 display the racial distribution (White, Black, and Hispanic) and the results of the LPA analysis for San Diego County and New York City, respectively. In the racial distribution maps, the intensity of each color represents the proportion of the corresponding racial group within each census tract. Darker shades indicate a higher concentration of a particular race, while lighter shades signify a lower concentration. These maps provide a visual representation of the spatial segregation patterns in both areas, highlighting areas where specific racial groups are more concentrated. The LPA results largely reflect the racial distribution patterns observed in the corresponding maps. This is more prominent in New York City than in San Diego County, with the distribution of Hispanics contributing to Class 2 (Blue), the distribution of Whites contributing to Class 1 (Red), Class 3 (Green), and Class 4 (Purple), and the distribution of Blacks contributing to Class 5 (Yellow).

5.2 Changes in network measures during COVID-19

The Kernel Density Estimation (KDE) plots in Figs. 4 and 5 highlight the impact of the COVID-19 lockdown on urban mobility patterns in San Diego County and New York City, respectively, through changes in degree centrality and closeness centrality distributions between 2019 and 2020. In both areas, the distributions for each centrality measure in 2019 exhibit consistency across different months from January to June, indicating stable mobility network structures. In 2020, particularly in April, represented by a red line in the plots, both areas experienced notable shifts in centrality distributions to the left. This shift, signaling a decrease in degree and closeness centrality values, illustrates a significant reduction in overall connectivity within the mobility networks and a decrease in the efficiency of information or resource flow. These changes are likely due to the lockdown measures imposed in response to the pandemic.

Figure 6 illustrates the variation in average network measures across different LPA classes over time. Overall, in April 2020, there was a decline in degree centrality, whereas betweenness centrality increased during the same period. Specifically, in San Diego County, the clustering coefficient for Class 3 (High Proportion White

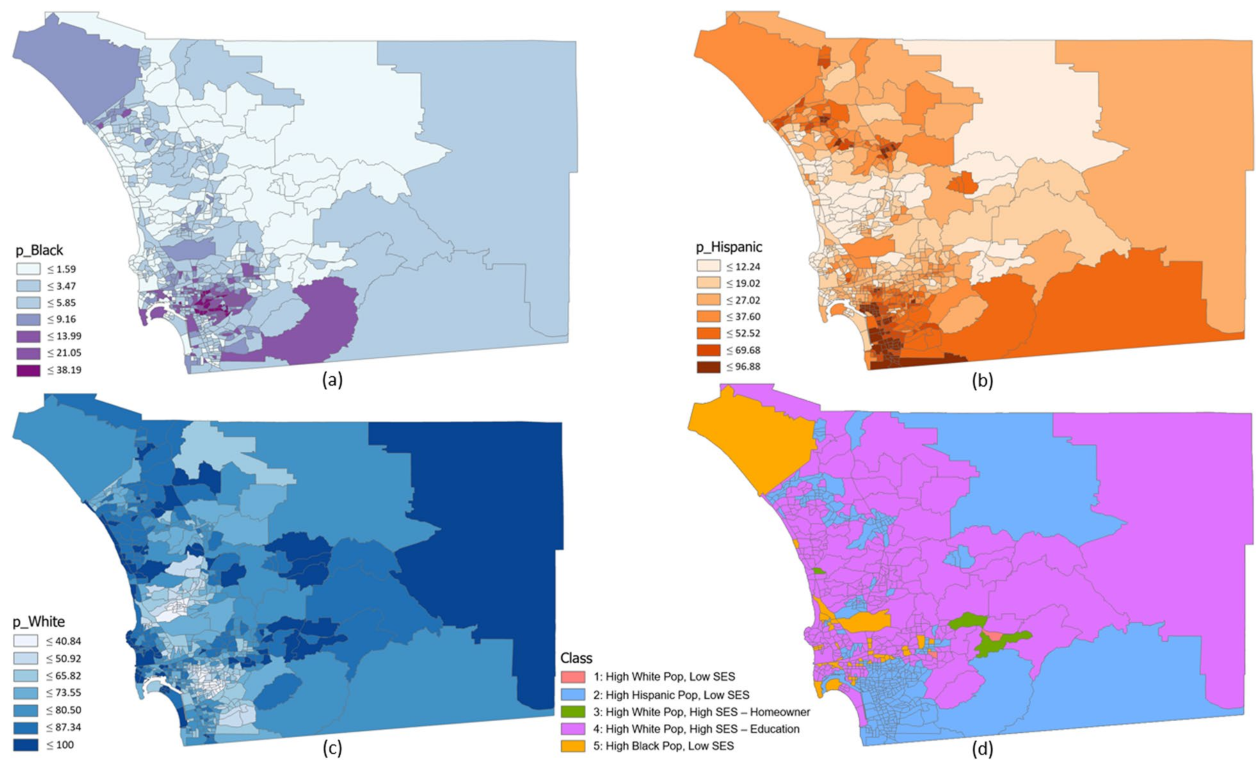

Fig. 2 Distribution of Race and LPA class in San Diego County. **a** Percentage of Black population, **b** Percentage of Hispanic population, **c** Percentage of White population, and (**d**) LPA Classification result. Darker shades indicate a higher concentration of a particular race, while lighter shades signify a lower concentration

with High SES - High Homeowners) witnessed a notable rise, distinct from other classes, suggesting a higher tendency for nodes within this class to cluster together. In addition, an increase in betweenness centrality may indicate a more significant role for specific nodes in facilitating communication or connectivity between disparate parts of the network.

5.3 Uncovering human mobility networks and hubs

Figures 7 and 8 display comparative maps of 2019 and April 2020 network measures in San Diego County and New York City, respectively. These figures illustrate the distribution of various network measures, including PageRank, eigenvector centrality, closeness centrality, and betweenness centrality. Each row contains two maps for a specific network measure: the left-side maps represent the average for all months in 2019, while the right-side maps show data for April 2020. The comparison highlights the changes in network centrality measures over time, with darker colors indicating higher values.

In San Diego County, areas with high values in PageRank and eigenvector centrality in 2019 included the Marine Corps Base Camp Pendleton, areas hosting four casinos, Montgomery-Gibbs Executive Airport, McClellan-Palomar Airport, LEGOLAND, Elfin Forest Recreational Reserve, San Diego International Airport, Mission Bay Park, and regions near the border. These hubs facilitated a large amount of flow and connectivity. The betweenness centrality map revealed areas that served as bridges within the network. Some areas consistently appeared dark across all maps, indicating their simultaneous role as high-mobility areas, hubs, and bridges.

In April 2020, during the COVID-19 pandemic, certain areas maintained high values as hubs, while others saw a reduction. For example, the area with four casinos no longer served as a hub. In contrast, areas such as the University of California, San Diego, and regions with three hospitals remained significant on the betweenness map. Additionally, rural areas in the East, where national parks are located, showed higher values in all centrality measures except closeness centrality, indicating increased mobility in these regions.

In New York City, 2019, data showed that areas with high centrality in PageRank and eigenvector centrality included two airports, the Co-op City, and various parts of Manhattan. The betweenness centrality map indicated that LaGuardia Airport, unlike JFK

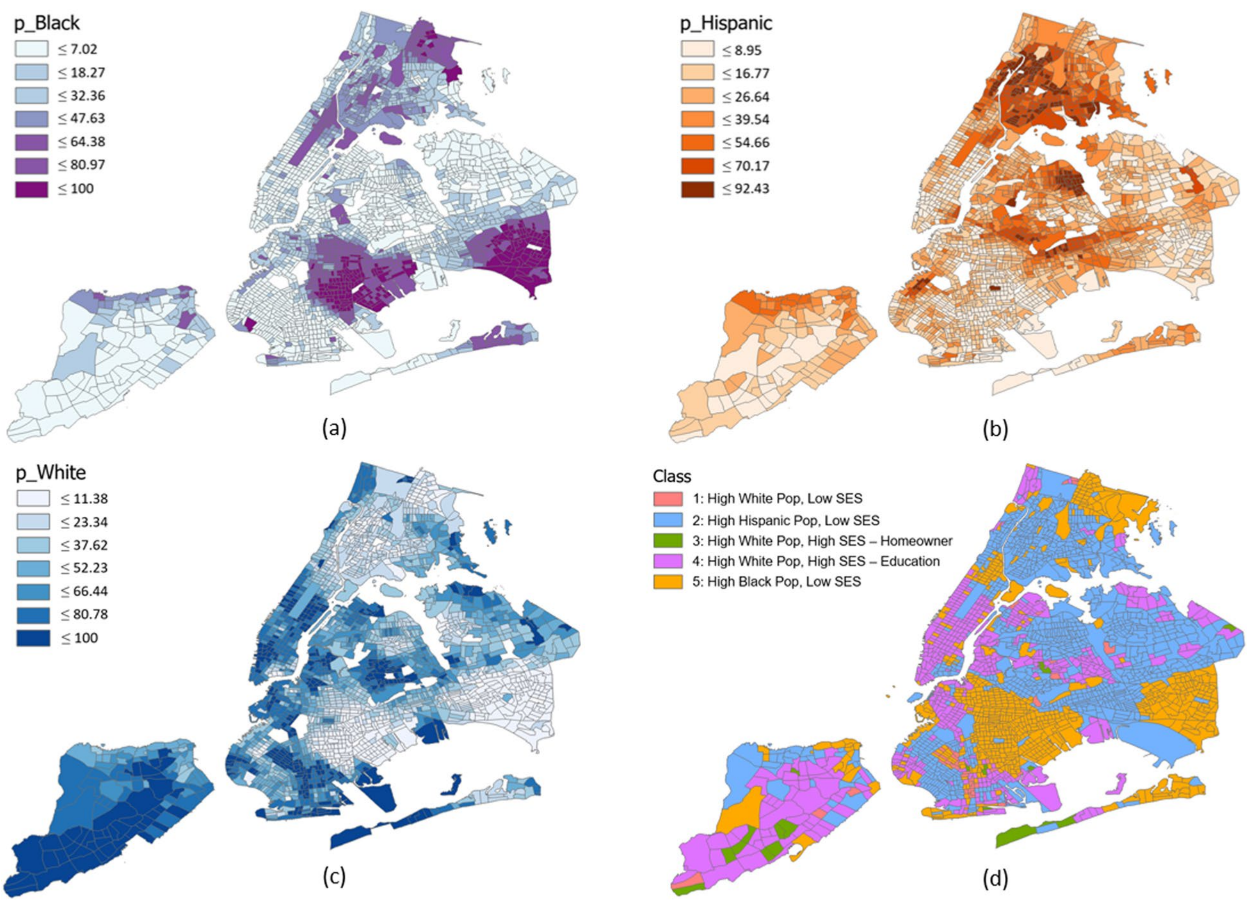

Fig. 3 Distribution of Race and LPA class in New York City. **a** Percentage of Black population, **b** Percentage of Hispanic population, **c** Percentage of White population, and (**d**) LPA Classification result. Darker shades indicate a higher concentration of a particular race, while lighter shades signify a lower concentration

International Airport, served as a bridge, likely due to its proximity to Manhattan.

By April 2020, Manhattan experienced a reduction in all four centrality measures—PageRank, eigenvector centrality, closeness centrality, and betweenness centrality—in most areas except Central Park. In contrast, Central Park, Prospect Park and Zoo, Botanical Garden, the Co-op city, and a region in the South Bronx with several parks exhibited a substantial increase in betweenness centrality. These areas also showed increased values in PageRank and eigenvector centrality, indicating their importance as hubs and bridges during the pandemic. Closeness centrality, however, revealed that most dark areas from 2019 had decreased values, appearing brighter in color. Additionally, LaGuardia Airport no longer served as a bridge, reflecting shifting mobility dynamics.

5.4 Socioeconomic associations with mobility networks during COVID-19

Both degree centrality and eigenvector centrality can reveal areas with higher mobility. The bar graphs in Fig. 9 show the percentage of nodes per class in the top 100 rankings for degree centrality (top) and eigenvector centrality (bottom) in San Diego County and New York City from January to June 2020. The graphs reveal an intriguing shift in node composition, particularly during March and April 2020. This period marks a significant downturn in overall mobility due to the stringent COVID-19 lockdown measures implemented globally. The graph distinctly illustrates an increase in the number of nodes classified as belonging to areas characterized by struggling Hispanic (Class 2) and Black populations (Class 5). Conversely, there is a noticeable decrease in the number of nodes from affluent,

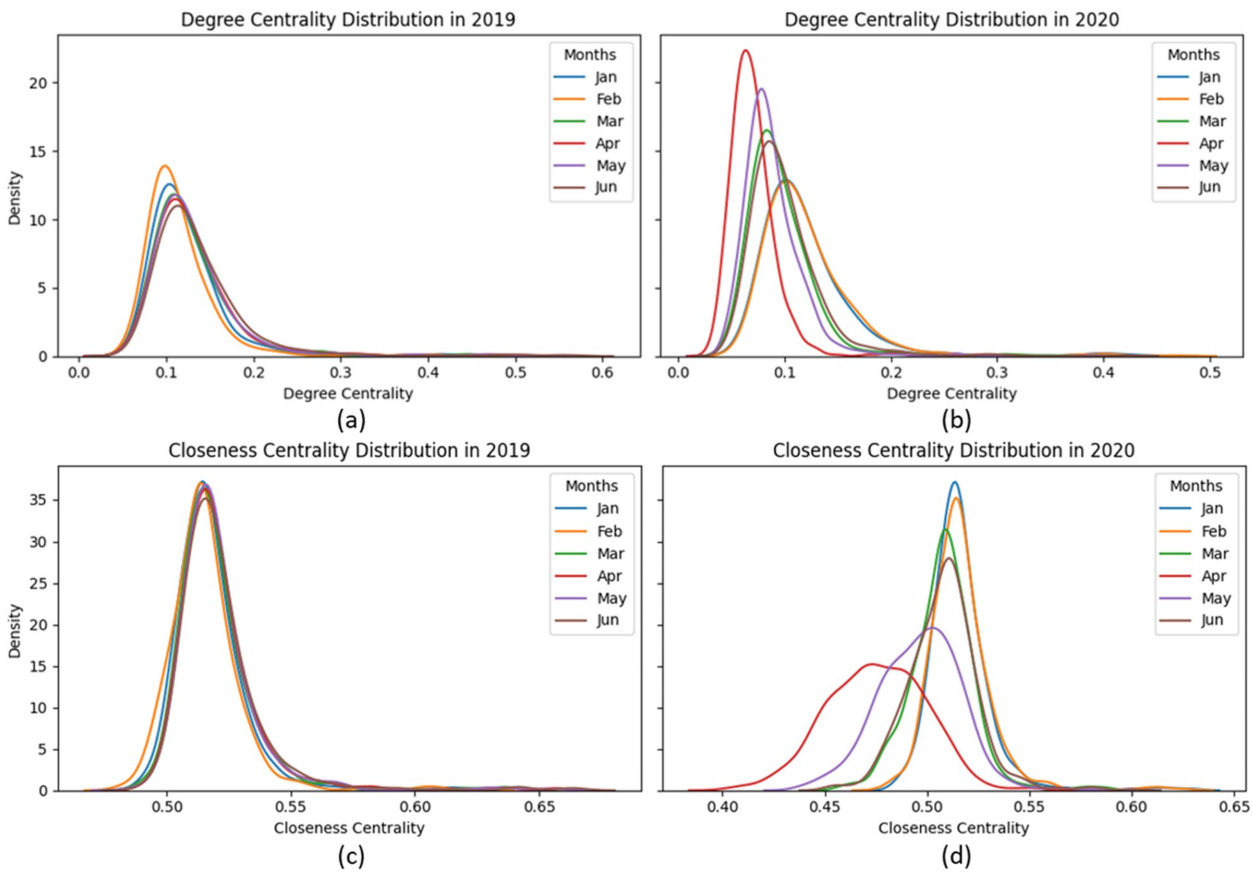

Fig. 4 Degree and closeness centrality distributions in San Diego County: **a** Degree Centrality, 2019; **b** Degree Centrality, 2020; **c** Closeness Centrality, 2019; **d** Closeness Centrality, 2020

predominantly White areas with high education attainment (Class 4) within the same top rankings. This increase and decrease pattern is observed in both areas.

The examination of the relationship between network measures and socioeconomic variables reveals insights into how social and economic factors interact within human mobility networks (see Fig. 10). This correlation heatmap shows the Pearson correlation coefficient between network measures (y-axis) and socioeconomic variables (x-axis). Among the five identified classes, Class 4, characterized by a high proportion of White residents coupled with high SES, presents a distinct pattern in its association with education levels. Specifically, network measures in this class are correlated with higher education attainment, such as possessing a bachelor's degree or higher. This correlation suggests that areas within the urban mobility network that serve as hubs—central nodes with high levels of connectivity—are more likely to be those with higher levels of educational attainment among their residents.

6 Discussion and conclusion

6.1 Key results and interpretation

This study examined human mobility networks and their changes during the COVID-19 pandemic in San Diego County and New York City using mobile phone data and census information. The findings provide key insights into the identified hubs, their relationship with SES, and the impact of the pandemic on mobility patterns.

By utilizing mobility data, the analysis revealed significant hubs and high-mobility areas in both San Diego County and New York City. In San Diego, key hubs included the Marine Corps Base Camp Pendleton, areas hosting casinos, major airports such as Montgomery-Gibbs Executive Airport and San Diego International Airport, Mission Bay Park, and regions near the border. In New York City, prominent hubs were located around major airports (JFK and LaGuardia), the Co-op City, the New York Botanical Garden, and various parts of Manhattan. These hubs were characterized by high

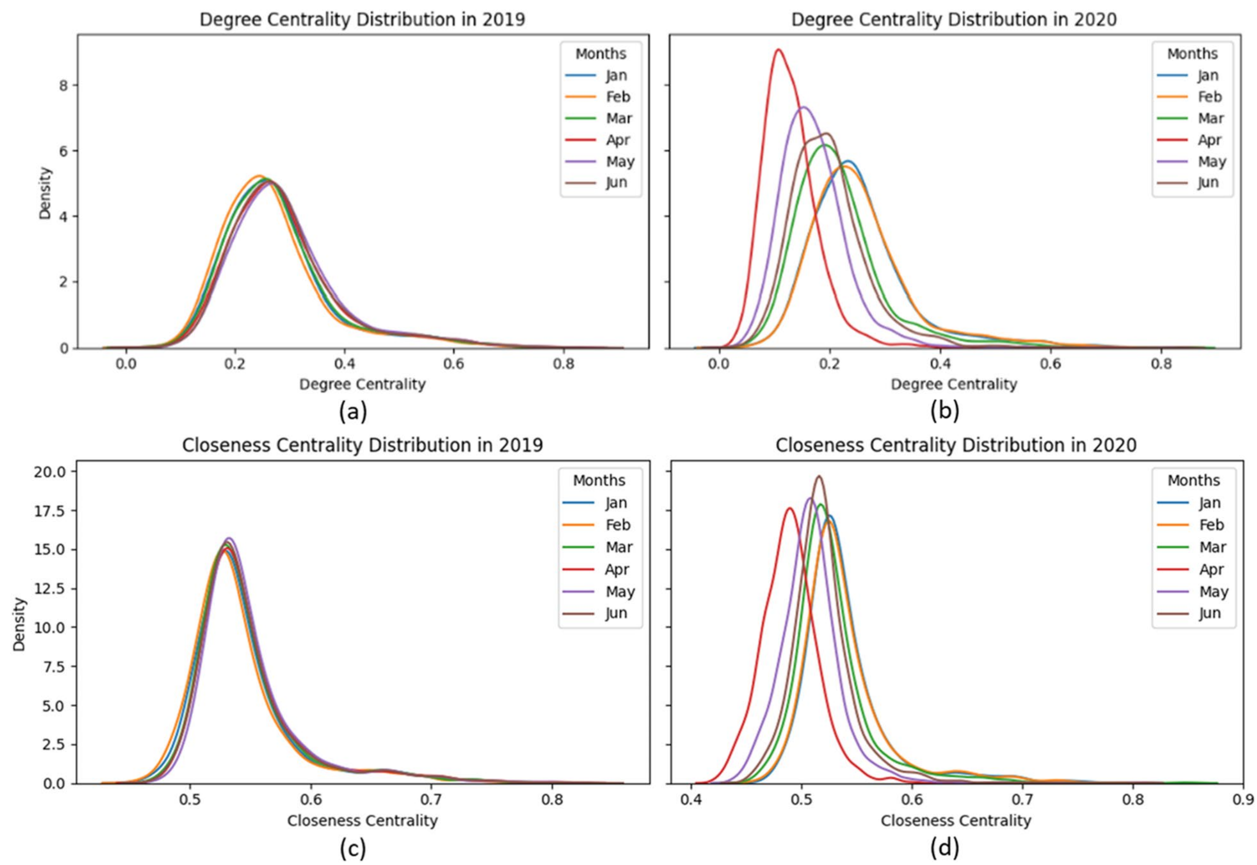

Fig. 5 Degree and closeness centrality distributions in New York City: **a** Degree Centrality, 2019; **b** Degree Centrality, 2020; **c** Closeness Centrality, 2019; **d** Closeness Centrality, 2020

connectivity, acting as central points for transportation and economic activities within the urban mobility network.

The study's LPA classification of census tracts revealed significant correlations between mobility patterns and socioeconomic status. The examination of the relationship between network measures and socioeconomic variables provides insights into how social and economic factors interact within mobility networks. Among the five identified classes, Class 4, characterized by a high proportion of White residents coupled with high SES and high education attainment, presents a distinct pattern in its association with education levels. Specifically, network measures in this class are correlated with higher education attainment, such as the possession of a bachelor's degree or higher. This correlation suggests that areas within the mobility network that serve as hubs—central nodes with high levels of connectivity—are more likely to be those with higher levels of educational attainment among their residents. This suggests that in certain socioeconomic contexts, higher educational attainment and SES significantly influence urban mobility networks. Higher education levels often correlate with greater economic resources, which can influence mobility patterns through increased access to transportation and a greater range of travel options. Furthermore, areas with a high concentration of highly educated individuals may host a variety of economic and social opportunities, such as employment centers, cultural institutions, and other amenities that attract a high volume of movement and connectivity. These findings underscore the role of socioeconomic factors in shaping mobility networks within Class 4. High SES areas, particularly those with higher educational attainment, tend to function as significant hubs within the mobility network.

The COVID-19 pandemic significantly altered mobility patterns, exacerbating existing inequalities. Higher SES groups were able to reduce their mobility more effectively, likely due to their ability to work remotely. In contrast, lower SES groups, including low-income workers engaged in face-to-face service jobs, maintained higher levels of mobility, increasing their exposure to the virus. This disparity was evident in the top 100 census tracts with high degree centrality and eigenvector centrality,

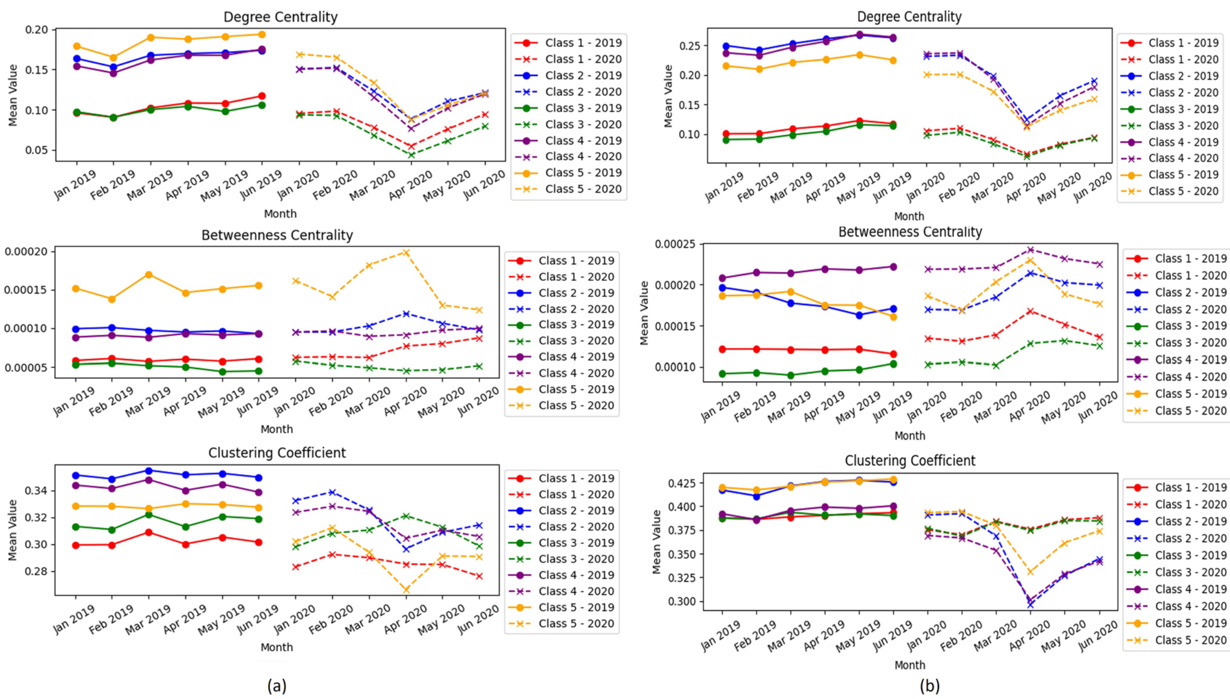

Fig. 6 Changes in network measures (degree centrality, betweenness centrality, and clustering coefficient) in (**a**) San Diego County and (**b**) New York City

where the proportion of nodes increased in Non-White, economically low SES groups and decreased in affluent, high education attainment, predominantly White tracts. The pandemic highlighted the resilience and indispensability of low-income service workers, who continued their commutes despite the overall reduction in movement, maintaining their presence in the mobility network's top centrality rankings. These workers, who disproportionately belong to Non-White groups (Bureau of Labor Statistics, 2020), had to continue working in person during the pandemic, despite the general reduction in movement. Their continued mobility was crucial to their livelihood and the functioning of essential services during the lockdown. Conversely, the decrease in mobility for affluent, high-education attainment, predominantly White areas suggests a higher capacity for remote work and adherence to lockdown measures. This shift underscores the stark contrast in how different communities experienced and navigated the early days of the COVID-19 crisis. This analysis reveals the significant role of socioeconomic and racial factors in urban mobility patterns, especially under crisis conditions. It underscores the importance of considering these factors in urban planning and policy-making to ensure equitable access to resources and support for all community segments, particularly those most adversely affected during crises.

Understanding the changes in these centrality measures is crucial for comprehending cities' resilience and adaptive capacity, particularly in response to disruptive events like the COVID-19 pandemic. These shifts in centrality measures can significantly impact urban connectivity, accessibility, and socioeconomic patterns. From the cases in San Diego County and New York City, we observed increased mobility in urban parks and rural areas where national parks are located. This trend underscores the shift in public preference towards outdoor recreational spaces during the pandemic, as people sought safe environments for exercise and leisure activities. These changes in mobility patterns and the roles of different urban areas highlight how certain areas adapted to new mobility demands, serving as critical connectors and hubs amidst widespread changes in urban activity. By evaluating these changes, urban planners can better understand how different areas adapt to crises and develop strategies to enhance urban resilience and sustainability. This understanding is essential for creating equitable urban environments that can withstand and recover from future disruptions.

6.2 Implications for urban planning and policy

The findings of this study have significant implications for urban planning and policy, particularly in the context

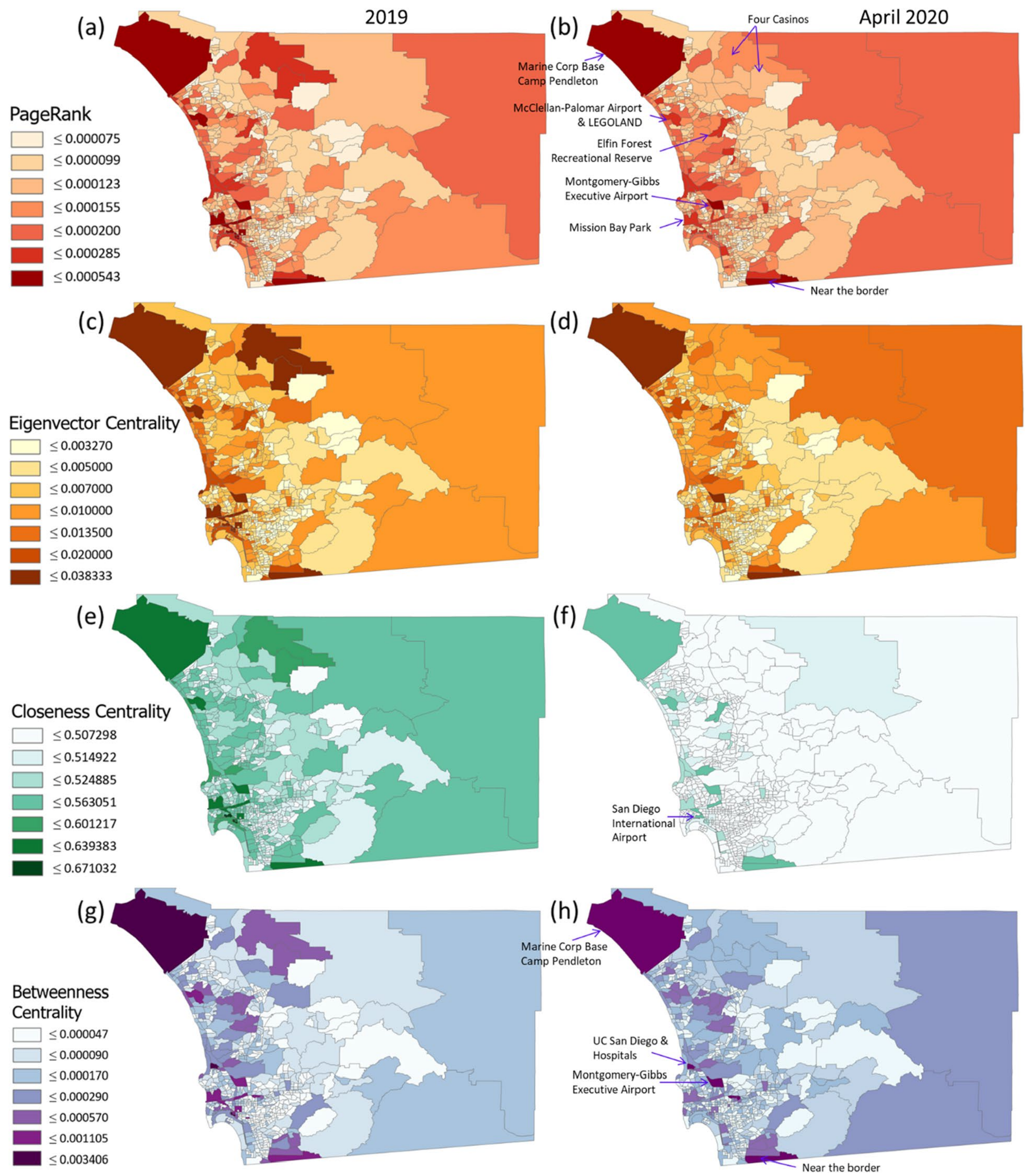

Fig. 7 Comparative maps of network measures for 2019 and April 2020 in San Diego County. Each row shows two maps for a specific network measure: PageRank, Eigenvector Centrality, Closeness Centrality, and Betweenness Centrality. The left maps (**a**, **c**, **e**, **g**) represent the average values for all months in 2019, while the right maps (**b**, **d**, **f**, **h**) depict the values for April 2020. This comparison highlights the changes in network centrality measures before and during the COVID-19 pandemic

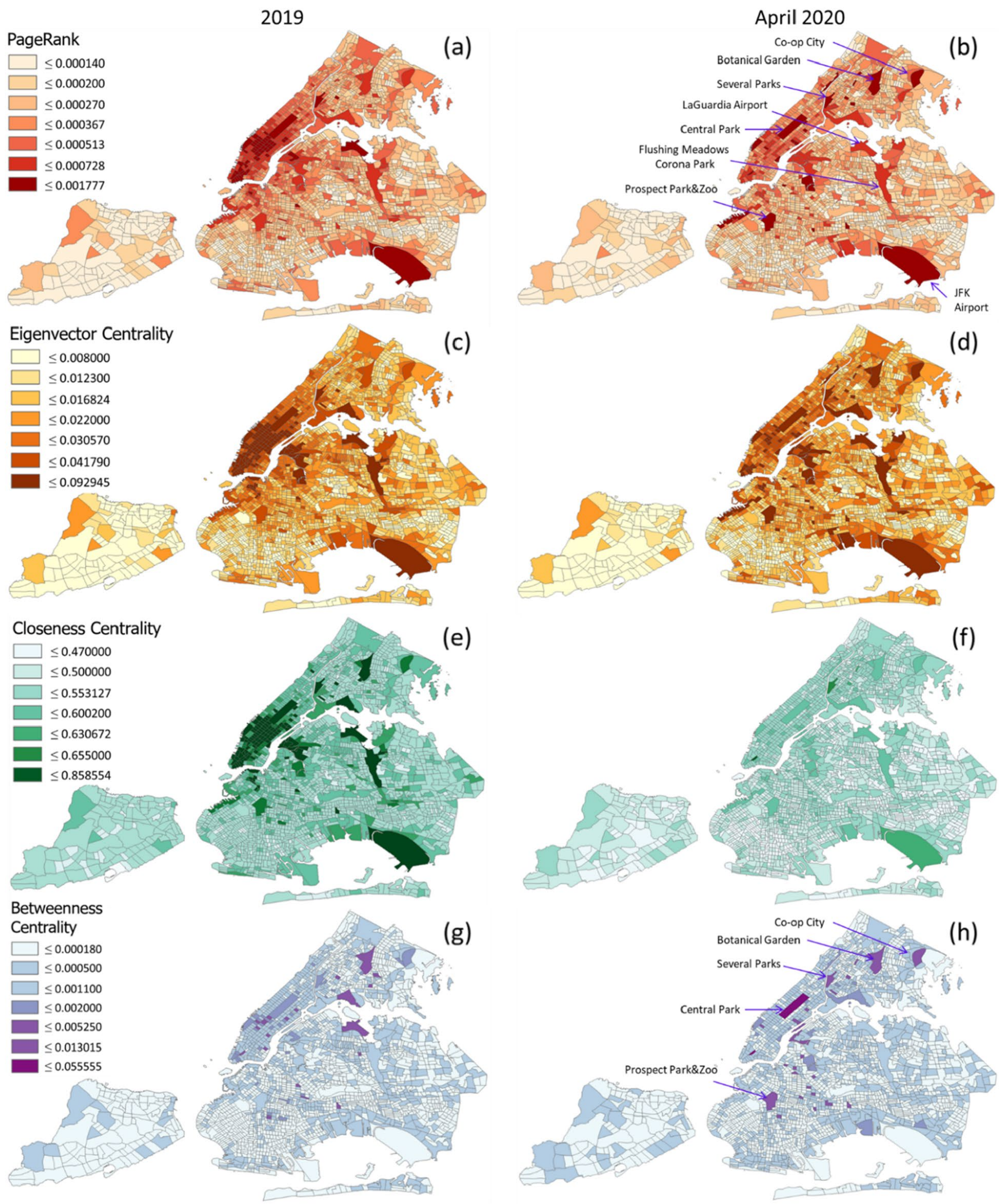

Fig. 8 Comparative maps of network measures for 2019 and April 2020 in New York City. Each row shows two maps for a specific network measure: PageRank, Eigenvector Centrality, Closeness Centrality, and Betweenness Centrality. The left maps (**a**, **c**, **e**, **g**) represent the average values for all months in 2019, while the right maps (**b**, **d**, **f**, **h**) depict the values for April 2020. This comparison highlights the changes in network centrality measures before and during the COVID-19 pandemic

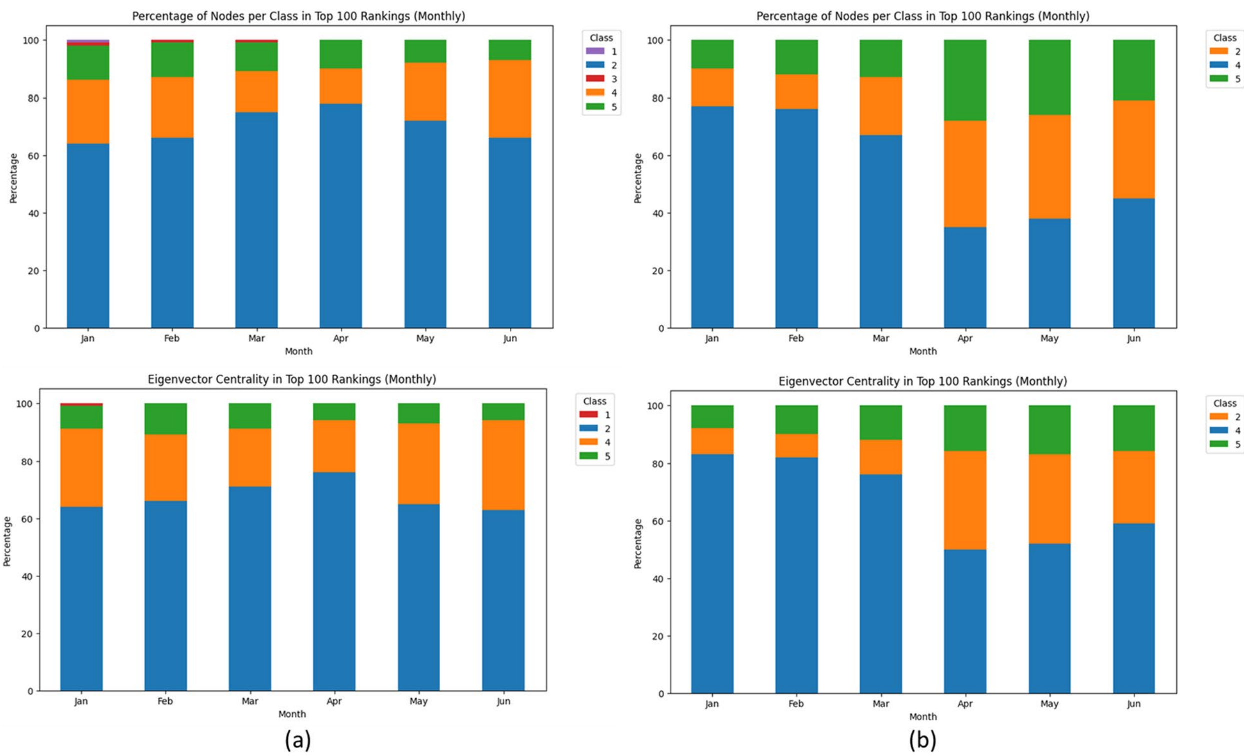

Fig. 9 Percentage of nodes per class in top 100 rankings for degree centrality (top) and eigenvector centrality (bottom): **a** San Diego County and (**b**) New York City

of future crises like pandemics. By applying a network science perspective, we mapped network measures and identified specific areas within cities with high mobility and their changes during COVID-19. This approach addresses the research gap where many studies provide overall mobility changes without focusing on specific areas within a city.

Urban planners can make informed decisions about transportation, infrastructure, and resource allocation by identifying hubs and bridges. Understanding which areas function as central points for transportation and economic activities can help plan more effective and resilient urban layouts. Our results revealed significant inequalities in mobility patterns during the pandemic, particularly highlighting that remote work was inaccessible for everyone. Lower SES groups, including low-income workers engaged in face-to-face service jobs, maintained higher levels of mobility, increasing their exposure to the virus. This underscores the need for urban planning and policy to address these disparities by supporting vulnerable populations. Targeted interventions such as job training programs, affordable housing initiatives, and enhanced healthcare access can help reduce these disparities and ensure equitable access to resources and opportunities.

Investigating the effectiveness of specific policy interventions aimed at reducing urban inequality and promoting social equity is essential. By evaluating the outcomes of different strategies, researchers can provide evidence-based recommendations for creating more inclusive and resilient urban environments.

Policymakers should implement comprehensive measures that address the root causes of social inequity, ensuring that all community segments benefit from urban infrastructure improvements. The insights gained from this study are crucial for preparing for future crises. Urban planners and policymakers can develop strategies to maintain essential connectivity while minimizing health risks by understanding how mobility patterns change during a pandemic. Ensuring that critical areas such as parks and open spaces are accessible and safe can help support public health and well-being during lockdowns or other restrictive measures.

Understanding human mobility and its changes is crucial for addressing the complex challenges facing cities today. By leveraging advanced geospatial data and analytical methods, researchers and policymakers can gain valuable insights into the interplay between physical and social factors, informing efforts to create more equitable and resilient urban environments. The COVID-19

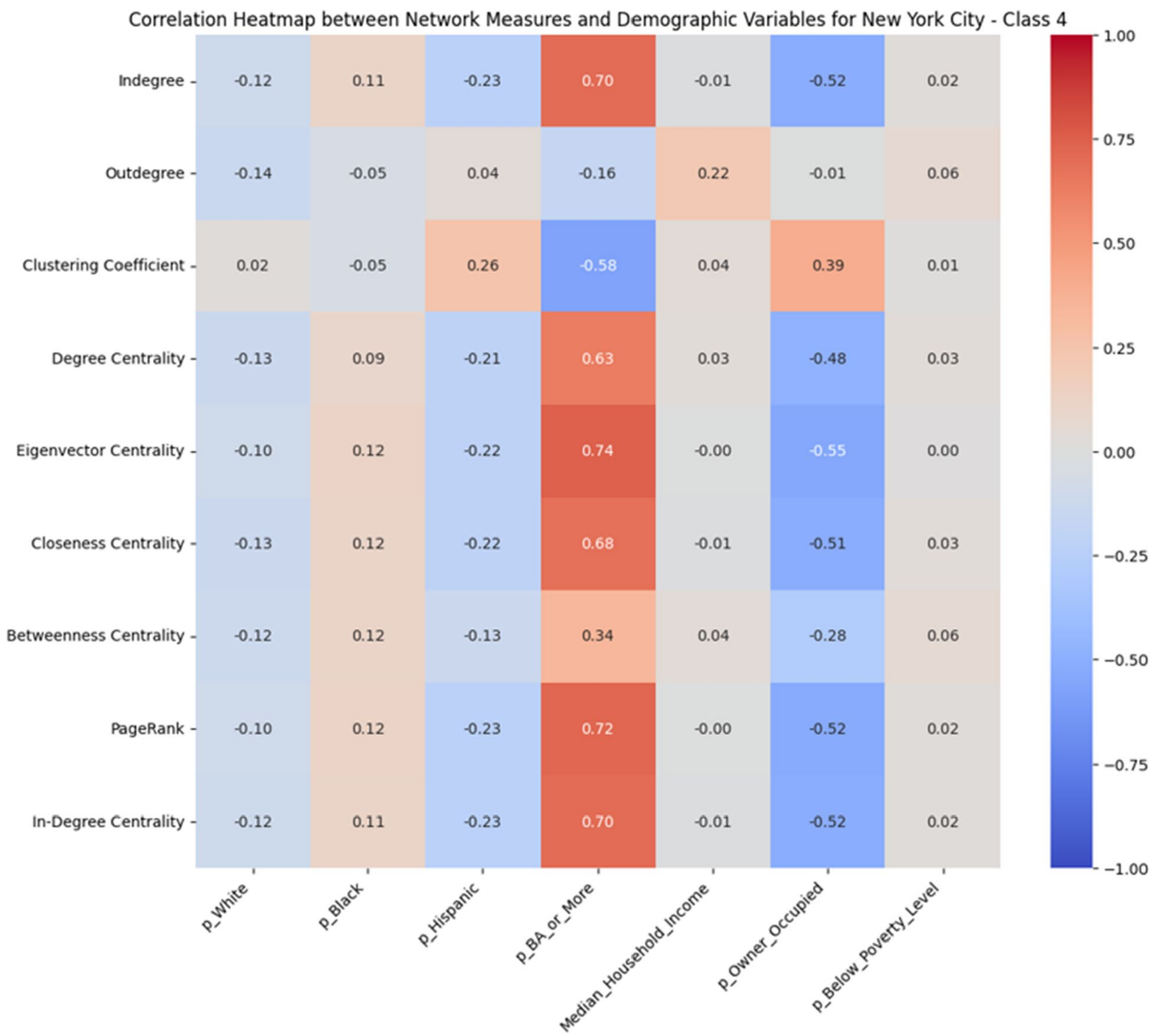

Fig. 10 Heatmap of Pearson correlation coefficient matrix: Network Measures and Socioeconomic Variables for Class 4 (High Proportion White and High SES - High Education Attainment) in New York City. The y-axis represents network measures, while the x-axis represents socioeconomic variables. Red indicates a positive correlation, while blue signifies a negative correlation

pandemic has underscored the importance of such efforts, highlighting the need for inclusive urban planning that considers the needs of all residents.

6.3 Limitations and future work

This study has several limitations. First, the study areas are limited to San Diego County and New York City. Each city has unique characteristics that can impact human mobility, such as city layout, transportation infrastructure, and demographic composition. Extending the analysis to other cities would help gain a broader understanding of mobility patterns across different contexts, thereby validating and generalizing the findings. Additionally, exploring the long-term impacts of the pandemic on socioeconomic disparities is crucial for understanding the lasting effects of COVID-19 on cities. Second, the LPA classified census tracts into five classes focused primarily on White, Black, and Hispanic populations in San Diego County and New York City. This focus excludes other demographic groups, such as Asian communities, whose experiences and segregation dynamics differ and are less represented in the historical literature on segregation.

While the study revealed significant inequalities in mobility changes among these classes, including Asian and other populations in the analysis may yield different results. Future research should incorporate a broader range of demographic groups to provide a more detailed understanding of mobility and segregation dynamics. Third, SafeGraph data, based on a sample of mobile devices, may only partially represent part of the population. Certain demographic groups, such as older adults or those without smartphones, may be underrepresented in the data. This limitation can affect the generalizability of the findings. Additionally, a challenge with this dataset is that it originates from a private company and is no longer available for further research, limiting the ability to replicate or extend the study using the same data source. Despite these limitations, SafeGraph's mobility data remains valuable for analyzing human mobility patterns and understanding the spatial dimensions of social distancing and its impact on communities. Future research could incorporate additional data sources to validate and complement the findings based on SafeGraph data.

Future research should explore the dynamic interplay between mobility patterns and socioeconomic factors. Longitudinal studies can provide deeper insights into how urban networks evolve over time and in response to different crises. Recommendations for urban planning include fostering community resilience, enhancing public spaces, and ensuring that all neighborhoods are well-connected and equipped to handle future disruptions.

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Authors' contributions
Conceptualization (Jaehee Park, Ming-Hsiang Tsou), Data collection & analysis, Writing- original draft preparation (Jaehee Park), Writing- review& editing, Supervision (Ming-Hsiang Tsou, Atsushi Nara, Somayeh Dodge, Susan Cassels).

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Availability of data and materials
SafeGraph's mobility data are not publicly available. Census data (5year, 2015-2019 American Community Survey) are available online.

Declarations

Competing interests
The authors declare they don't have competing interests.

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