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# COVID-19 impacts on non-work travel patterns: A place-based investigation using smartphone mobility data

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**Abstract**
The COVID-19 pandemic has brought unprecedented changes to our mobility. It has not only changed our work-related travel patterns but also impacted leisure and other utilitarian activities. Non–work-related trips tend to be more seriously affected by the neighborhood/contextual factors such as socioeconomic status (SES), and destination accessibility, and COVID-19 impact on non-work trips may not be equal across different neighborhood SES. This study compares non–work-related travel patterns between the pre- and during COVID-19 pandemic in the City of El Paso, Texas. By utilizing smartphone mobility data, we captured the visitation data for major non-work destinations such as restaurants, supermarkets, drinking places, religious organizations, and parks. We used Census block groups ($n$ = 424) within the city and divided them into low- and high-income neighborhoods based on the citywide median. Overall, the total frequency of visitations and the distances traveled to visit these non-work destinations were influenced by the COVID-19 pandemic. However, significant variations existed in their visitation patterns by the type of non-work destinations. While the overall COVID-19 effects on non-work activities were evident, its effects on the travel patterns to each destination were not equal by neighborhood SES. We also found that COVID-19 had differently influenced non-work activities between high- and low-income block groups. Our findings suggest that the COVID-19 pandemic may exacerbate neighborhood-level inequalities in non-work trips. Thus, safe and affordable transportation options together with compact and walkable community development appear imperative to support daily travel needs for various utilitarian and leisure purposes, especially in low-income neighborhoods.

**Keywords**
Travel behavior, visiting patterns, COVID-19, inequality, place-based analysis, mobile-phone data

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## Introduction

Mobility is a critical element of daily living, independence, health, and quality of life. Abundant research has been conducted on travel behaviors, and their relations to land uses with different densities and destinations. Accessibility metrics refer to the ease of reaching destinations, which are used to help guide transportation and land use planning, equity analyses, and policy decisions based on the relationship between people and places (Saif et al., 2019; City of El Paso, 2020). The majority of transportation research on accessibility metrics has focused on access to jobs and spatial mismatch between work-related destinations and homes of the job seekers (Grengs, 2010; Yeganeh et al., 2018). However, commuting to work does not represent people's daily travel patterns which include many other important destinations, such as recreational facilities, grocery stores, and restaurants (McCahill, 2018).

The spread of coronavirus disease 2019 (COVID-19) has disrupted people's daily travel and social activities, as reported by many recent studies (Beck and Hensher, 2020; Saha et al., 2020; Bourdas and Zacharakis, 2020; Huang et al., 2020). For example, Sehra et al. (2020) examined cell phone location data and witnessed greater reductions of cell phone activities in the workplace and retail, while observing greater increases of activities at home. According to Beck and Hensher (2020), approximately 78% of the survey participants in Australia have made multiple changes to their weekly travel patterns (e.g. reductions in overall travel, in travel by private cars and public transport, in travel for commuting, social/recreational purposes, and education/childcare). Saha et al. (2020) analyzed the impact of COVID-19 lockdown in India and observed a significant decrease in mobility trends across different categories of places, including retail and recreation, transit stations, and workplaces. As of 31 January 2021, the COVID-19 Community Mobility Report from Google shows decreases in all categories except residential compared to before COVID-19: transit stations (−30%), workplaces (−23%), retail, and recreation (−15%), and parks (−13%) (Google LLC, 2022). However, the long-term impacts of COVID-19 on visitations to specific non-work locations such as food, merchandise, and sports are not known. In addition, only a few studies reported patterns of potential recovery in travel activities and behavior after the travel restrictions were removed (Van Wee and Witlox, 2021; Ding et al., 2021).

Previous studies showed that people from low-income households face more daily mobility challenges compared to other income groups. As transport constitutes approximately 16% of an average household expenditure based on the U.S. Bureau of Labor Statistics (BLS) Consumer Expenditure Surveys (CE) 2020 (Bureau of Labor Statistics, 2021), those in low-income areas with a lack of public transportation systems face challenges when accessing jobs, goods and even community services, such as schools and groceries (Lawson, 2018; Reuscher et al., 2017). According to the 2017 National Household Travel Survey (NHTS), lower-income individuals tend to walk, bike, or use public transit for 21% of their trips, while only 13% of higher-income individuals do the same (Federal Highway, 2017). During the COVID-19 pandemic, we witnessed less travel decline among less-educated and lower-income groups while we saw large average declines in overall travel (all income groups) since the travel restrictions, including in the use of public transit (Dueñas et al., 2021; Ruiz-Euler et al., 2020; Fraiberger et al., 2020). In other words, this is referred to as the mobility gap—seeing the difference in the drop of mobility rates between high- and low-income groups (Ruiz-Euler et al., 2020).

With the advancement of mobile devices, social media, cloud computing, and Artificial Intelligence, large-scale individual-level and location-based data have been widely available through mobile-phone applications enabling place-based studies on user mobilities and experiences (Prestby et al., 2020; Ye et al., 2021; Song et al., 2022b). These automatically collected data can reveal behavioral patterns and reach populations who do not typically participate in research studies, and therefore offer opportunities to uncover new environmental, social, and personal factors that drive health and well-being (Hicks et al., 2019; Fernandez et al., 2022). In this study, we use SafeGraph (SafeGraph, 2020), an anonymized cell phone location dataset merged with machine-generated and human-verified Point of Interest (POI) boundaries, to study mobility patterns related to non-work activities. With 6 million POI listings and 19 million smartphone devices collected in the US, SafeGraph has shown that its aggregated mobility trends match Google mobility data, and it does not systematically overrepresent individuals in specific counties, racial compositions, and income or education levels (SafeGraph, 2019). SafeGraph has been used to support various research topics in economics, public health, transportation, urban planning, etc. It has been used to study parking in business locations and parks in cities (Gao et al., 2019; Song et al., 2022a), COVID-19 transmissions and reopening strategies (Chang et al., 2021), social distancing mobility adaptation (Lio et al., 2021; Huang et al., 2021), unhealthy eating patterns (Ashby, 2020), political and social mobilization (Van Dijcke and Wright, 2020).

By utilizing smartphone-based mobility data, this study compares non–work-related travel patterns between pre- and during COVID-19 for the US–Mexico border city of El Paso, Texas. Popular utilitarian and leisure destinations (i.e. supermarkets, merchandise stores, restaurants, liquor stores, drinking places, religious organizations, parks) were included as the non–work-related destinations in this study. We used the neighborhood-level analysis and focused on the travel pattern differences by neighborhood SES. Three research questions related to COVID-19 impacts on non–work-related travel patterns were answered:

1. How far and frequently do people travel to different non–work-related destinations?
2. How did the travel distances and visitation frequencies change after the COVID-19 outbreak?
3. Are there any mobility disparities between high- and low-income neighborhoods?

Answers to the abovementioned questions can help understand the magnitude and disparities of the impact that COVID-19 has brought to the mobility of populations, especially in a city with high proportions of Hispanic and economically disadvantaged populations. It offers insights for future economic development and urban planning policies to improve daily mobility needs during and beyond pandemics like COVID-19.

## Methodology

### Study location

We used the city of El Paso, Texas located along the US–Mexico border as the study site. El Paso has a land area of 259 square miles and a population of 678,815(U.S. Census Bureau, 2020) as the 23rd largest city in the US and the 6th in Texas. As a major Mexico–US border city, El Paso has a large proportion of Hispanic population (81.4%). The median household income in 2019 was $47,568, significantly lower than the US average of $69,560 (U.S. Census Bureau, 2020). Only 25.1% held a bachelor's degree or above according to the 2019 US Census, which is higher than the national average of 22.5%. About 7.4% of its residents live in a household without a car, compared to 8.7% at the national level (Maciag, 2017). The homeownership rate in El Paso was 58.9% (U.S. Census Bureau, 2020). In terms of the unemployment rate, the early phase of the COVID-19 pandemic had dramatically changed job security. In September 2019, the unemployment rate of the city was 3.7%, which has increased to 14.3% in April 2020 right after the national declaration of the COVID-19 pandemic and gradually decreased to 8.2% in September 2020 according to the U.S. Bureau of Labor Statistics.

## Mobility data

Two datasets provided by SafeGraph included (1) "Core Point of Interests (POI)" including place-based information such as name, location, brands, address, and category (based on North American Industry Classification System by US Census Bureau) for 6.1 million locations in the US; (2) "Place Patterns" providing information of weekly travels for users of each POI including the distance traveled and the number of visitors from each home or origin Census block group (BG), which are the main measures in this study.

SafeGraph defines a device's home BG by tracking mobile devices that stay overnight at a Geohash-7 space (153m x 153m) as their common places between 6 PM and 7 AM over a previous 6-week period. For privacy considerations, if a home BG only has less than five devices detected per month going to a POI, the records of that home BG are excluded. Any visitor records (either POI or BG) smaller than four are counted as four. A Laplacian noise algorithm is applied to certain SafeGraph variables (Safegraph, 2022). These methods will produce slightly different numbers than reality to protect users, so people won't be able to find any personally identifiable information through SafeGraph. Other limitations that Safegraph fails to track correctly may include people who leave home without their phones and frequently change sleep locations. To reduce the impact of these potential measurement errors on our final results, we focus on patterns over a long timeframe (about 3 years) which should generate similar statistical properties to real situations when focusing over a long timeframe (Chiou and Tucker, 2020).

On 13 March 2020, a national emergency was declared in the US due to the COVID-19 outbreak, and the World Health Organization declared the global spread of COVID-19 as a pandemic on 11 March 2020. Accordingly, the city and county of El Paso declared a state of emergency on 13 March 2020 (City of El Paso, 2020). Since the national emergency declaration, the federal and state governments have released multiple guidelines for individual safety and prevention from COVID-19 (United States, 2020; Adams, 2021). From March to June of 2020, a series of guidance, orders, and restrictions on mass gatherings, public spaces, workplaces, and businesses have been implemented. However, by early July of 2020, all restrictions on the POIs included in our dataset have been terminated. To make more comparable comparisons, we define the pre-COVID period as September 2019 to February 2020. The post-COVID outbreak period was from September 2020 to February 2021 when all travel restrictions were lifted. Moreover, only the weekend mobility records were used in this study to mitigate the confounding effects of commuting and work-related activities during workdays.

As Figure 1 shows, 1,524 POIs (as place destinations) in eight categories in the city of El Paso were included. Overall, the POIs in this study represent non-work locations for foods, outdoor and recreational activities, shopping, social and spiritual events, etc. SafeGraph includes "parent" POIs that geographically overlap with their "child" POIs. For instance, a shopping mall as a parent POI may include other stores as child POIs located within the shopping mall. To avoid double-counting errors and given the focus on the individual destinations in this study, all "parent" POIs are deleted. Home BGs outside of El Paso are excluded to focus on daily and local travel behaviors. Weekly smartphone travel records of home BG (origin) to POI (destination) visitations were collected with a total of 503,961 observations. Each week, SafeGraph adjusts its device samples for every BG. For all data periods, the sampling rates (device-to-population ratio) for all BGs follow a normal distribution with a 4.2% average. A random pick of a BG also shows a normal distribution of its sampling rate throughout our study periods.

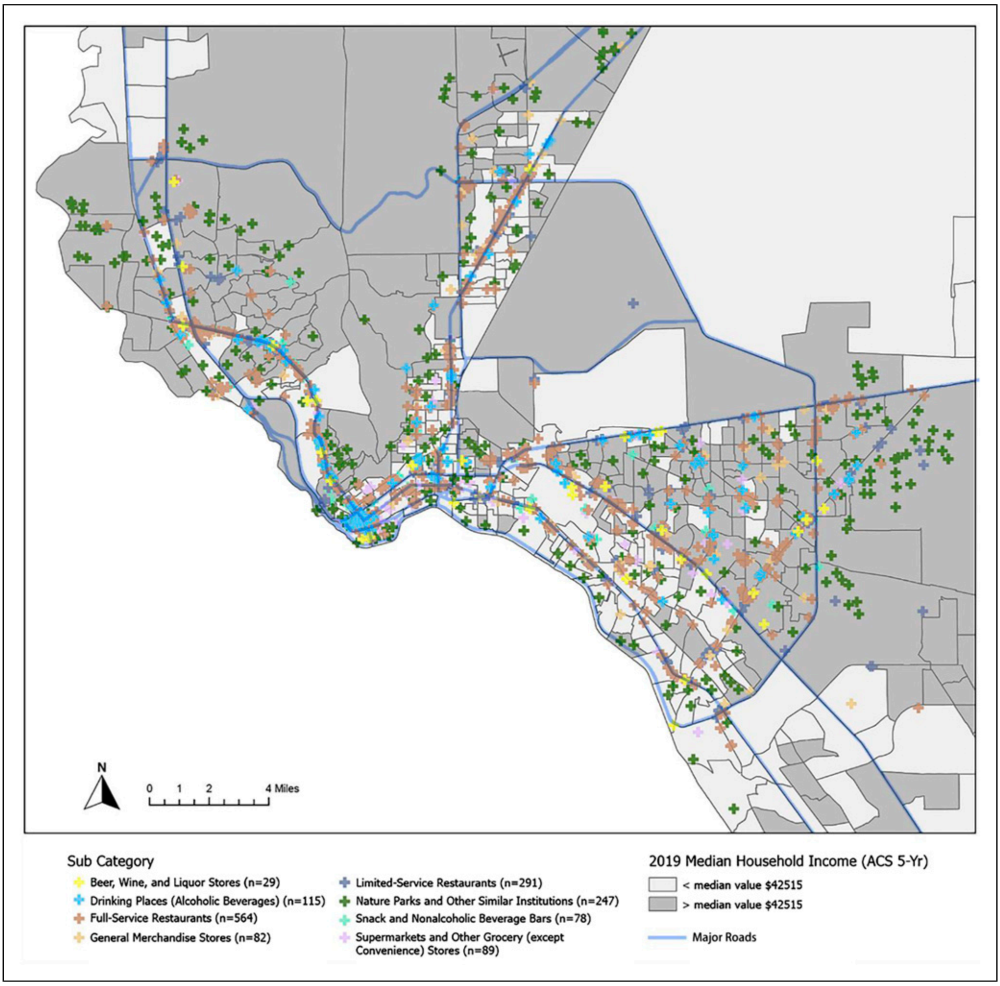


**Figure 1.** Point of interests (POI) locations.

## *Data processing methods*

To understand the travel patterns for different destinations, we specified aggregated measures at the POI category level that estimate POI visitors, travel distances, and proximities to home BGs. A POI category refers to a group of POIs designated by North American Industry Classification System as the same and a total of eight POI categories are included in this study.

*Point of interest category visitation.* SafeGraph provides weekly data on the number of smartphone signals detected from the home BG to a POI. However, these numbers don't represent the actual number of visitors to the POI since the BG device sampling rate varies every week and across the BGs. Similar to previous studies (Jay et al., 2020), we account for temporal (weeks) and spatial (BGs) variation in the device-to-population ratio for each BG by using equation (1.1) to estimate the total number of real visitors from home BG to a POI. Equation (1.2) is for aggregating total visitor numbers of a POI. Equation (1.3) is used to estimate the average number of visitors from each BG to a POI category

$$Visitors\_POI\_BG_{i,k,t} = \left(Visitors\_SG\_POI\_BG_{i,k,t} * POP_j\right) / SGD_{i,t} \tag{1.1}$$

where i represents the individual BG that the study included; k represents the individual POI that the study included. $Visitors\_POI\_BG_{i,k,t}$ refers to the visitor number from $BG_i$ to $POI_k$ during the $t^{th}$ weekend of our study period; $SVisitors\_SG\_POI\_BG_{i,k,t}$ refers to the number of smartphone devices from $BG_i$ to $POI_k$ during the $t^{th}$ weekend of our study period, provided by SafeGraph; $POP$ refers to the total population of the $BG_i$; $SGD_{i,t}$ refers to the total device number sampled for $BG_i$ at the $t^{th}$ weekend of our study, provided by SafeGraph

$$POI\_Visitors_{k,t} = \sum_{i=0}^{n} Visitors_{i,k,t} \tag{1.2}$$

where $POI\_Visitors_{k,t}$ refers to the total visitor number of $POI_k$ from all BGs during the $t^{th}$ weekend; $Visitors_{i,k,t}$ (calculated by equation (1.1)) refers to the visitor number from $BG_i$ to $POI_k$ during the $t^{th}$ weekend; n refers to the number of BGs that have traveled to $POI_k$ during the $t^{th}$ weekend

$$Total\_Visitors\_per\_BG_{j,t} = \sum\nolimits_{k \in j} POI\_Visitors_{k,t} \ / \ Num\_BG \tag{1.3}$$

where $Total\_Visitors\_per\_BG_{j,t}$ refers to the total visitor number per BG to all POIs in category j during the $t^{th}$ weekend; $POI\_Visitors_{k,t}$ (calculated by equation (1.2)) refers to the total visitor number of $POI_k$ from all BGs during the $t^{th}$ weekend; $POI_k$ belongs to category j. $Num\_BG$ is the total number of BGs included in the calculation.

*Point of interest category distance traveled.* We estimate the distance users traveled for each POI by calculating the network distances between all pairs of home BG centroids to POIs. Street network distances are more accurate in capturing the actual distance people traveled than the Euclidean distances (straight line). To account for the varying popularity of each POI, we weighted the aforementioned network distances based on the weekly home BG visitors to the POIs using equation (2.1) to calculate the weighted distance traveled per POI. This method gives higher weights to distances of the BG-POI pairs that have larger visitor counts. Using a similar approach, we then aggregated category-level distances traveled by weighting all POI distances traveled in the category based on the corresponding total POI visitor counts as shown in equation (2.2)

$$Distance\_POI_{k,t} = \frac{\sum_{i=0}^{n} Visitors_{i,k,t} * Distance_{i,k}}{\sum_{i=0}^{n} Visitors_{i,k,t}} \tag{2.1}$$

where $Distance\_POI_{k,t}$ refers to the visitor weighted distance traveled for POI k during the $t^{th}$ weekend; $Visitors_{i,k,t}$ (calculated by equation (1.1)) refers to the visitor number from $BG_i$ to $POI_k$ during the $t^{th}$ weekend; $Distance_{i,k}$ refers to the network distance between $BG_i$ centroid and $POI_k$

$$Distance\_Category_{j,t} = \frac{\sum_{k \in j} POI\_Visitors_{k,t} * Distance\_POI_{k,t}}{\sum_{k \in j} POI\_Visitors_{k,t}} \tag{2.2}$$

where $Distance\_Category_{j,t}$ is the visitor weighted distance traveled for POI category j during the $t^{th}$ weekend. $POI\_Visitors_{k,t}$ (calculated by equation (1.2)) refers to the total visitor number from $POI_k$ (belongs to category j) at the $t^{th}$ weekend. $Distance\_POI_{k,t}$ is the visitor weighted distance traveled for $POI_k$ during the $t^{th}$ weekend calculated by equation (2.1).

Another analysis involves the calculation of the proximity to different POI categories to represent their physical accessibility. Given the fact that people are more likely visit places closer to them, we consider the proximity of a BG to a POI category equals the distance between the BG centroid and its nearest POI of the category. Then by weighting all these nearest distances with the BG populations, we developed our proximity measure for BGs went to the POI category using equation (3) below. It is a representation of an assumed scenario that all home BG populations visit their nearest category POI every weekend

$$Cat\_prox_j = \frac{\sum_{i=0}^{n} Near\_Dist_{ij} * Pop_i}{\sum_{i=0}^{n} Pop_i} \quad (3)$$

where $Cat\_prox_j$ is the population weighted proximity traveled for POI category j. $Near\_Dist_{ij}$ is the distance between $BG_i$ and its nearest POI in category j. $Pop_i$ is the population of $BG_i$. n is the total number of BGs in our study.

## Results

### Data introduction

Table 1 provides the basic aggregated information about the POI data, including the total number of POIs and a few specific examples of POI names in each POI category. The "General merchandise stores" category includes major retailers like Walmart and Dollar Generals with a high volume of visitors. Eating places including "Full-service restaurants," "Limited-service restaurants," and "Drinking places" are popular POIs, like in most urban communities. The "Limited-service restaurants" category is dominated by fast-food restaurants in our study community of El Paso, Texas.

### Overall COVID-19 impacts on POI visitation patterns

We compare pre- and during COVID-19 data using a two-sample t-test (Snedecor and Cochran, 1989) to test if two population means are equal. From Table 2, all categories showed significantly lower numbers of visitors during COVID-19, with the two-sample t-test results showing a $p$-value < 0.05. "General merchandise stores," "Full-service restaurants," "Limited-service restaurants," and "Nature parks and other similar institutions" have higher visitor counts than the other categories. Regarding distance traveled, most categories have shown a significant decrease ($p$-value < 0.05) in

**Table 1.** List of POI categories and descriptions.

| Category | # of POIs included | Example POIs |
|---|---|---|
| General merchandise stores | 82 | Dollar General, Dollar Tree, Walmart |
| Supermarkets and other grocery (except convenience stores) | 89 | Sprout Farmers Market, JC Grocery, Albertsons |
| Beer, wine, and liquor stores | 29 | Barrel House Liquor, WB Liquors & Wine |
| Full-service restaurants | 564 | China House, Tortas Grill, Lulu's Café |
| Limited-service restaurants | 291 | Domino's Pizza, Wendy's. Whataburger |
| Drinking places (alcoholic beverages) | 115 | Jacky's Sports Bar, Kinda Classy Bar |
| Snack and nonalcoholic beverage bars | 78 | Starbucks, Milky's ice Cream |
| Nature, parks, and other similar institutions | 247 | Aviators Park, Estrella Park, Feather Lake |

**Table 2.** Visitation and distance traveled comparison between pre- and during COVID-19.

| COVID effects | POI visitation | | | | | Distance traveled (mi) | | | |
|---|---|---|---|---|---|---|---|---|---|
| Category of POI | During COVID-19* | Pre-COVID-19* | *t* (during-pre) | *p* | Proximity dist. (mi) | During COVID-19* | Pre-COVID-19* | *t* (during-pre) | *p* |
| General merchandise stores | 197.18 (113.06) | 233.67 (61.88) | −2.815 | 0.007 | 1.30 | 1.37 (0.03) | 1.35 (0.02) | 2.505 | 0.016 |
| Supermarkets and other grocery stores[a] | 43.00 (24.35) | 51.54 (9.36) | −3.293 | 0.002 | 1.34 | 1.44 (0.10) | 1.40 (0.04) | 1.790 | 0.080 |
| Beer, wine, and liquor stores | 5.22 (3.57) | 8.34 (2.90) | −6.612 | 0.000 | 2.05 | 1.81 (0.24) | 1.55 (0.22) | 3.843 | 0.000 |
| Full-service restaurants | 196.57 (113.36) | 335.59 (64.33) | −10.588 | 0.000 | 0.94 | 1.79 (0.08) | 1.83 (0.03) | −2.545 | 0.014 |
| Limited-service restaurants | 205.92 (112.98) | 261.6 (49.83) | −4.519 | 0.000 | 1.04 | 1.46 (0.07) | 1.60 (0.03) | −8.820 | 0.000 |
| Drinking places (alcoholic beverages) | 17.49 (12.71) | 46.4 (12.09) | −15.926 | 0.000 | 1.55 | 2.00 (0.19) | 2.05 (0.11) | −1.084 | 0.284 |
| Snack and nonalcoholic beverage bars | 40.04 (23.97) | 47.98 (14.2) | −2.821 | 0.007 | 1.55 | 1.68 (0.16) | 1.75 (0.15) | −1.458 | 0.152 |
| Nature, parks, and other similar institutions | 97.16 (74.24) | 127.65 (30.01) | −3.827 | 0.000 | 0.84 | 1.85 (0.10) | 1.96 (0.11) | −3.431 | 0.000 |

*Weekly visitors per block group | a: except convenience stores.

the distance traveled (4 out of 8 categories). The only significant increase in distance traveled is for "General merchandise stores." "Full-service restaurants," "Limited-service restaurants," and "Supermarkets and other grocery stores" are the stable categories that did not change significantly after the COVID-19 outbreak.

"Beer, wine, and liquor stores" is the highest on average proximity measures, suggesting that these POIs in our study community are located closer to the origins (BGs) than other POIs. "Nature, parks and other similar institutions," "Full-service restaurants," and "Limited-service restaurants" are categories with the lowest proximity measures, suggesting lower accessibility to these destinations from user home BGs.

## *Differential impact of COVID-19 on POI visitation patterns by neighborhood income levels*

We use the median household income of El Paso ($42,515) to define low versus high-income BGs and aggregate their mobility data for each POI category. Figure 2 plots the total weekly visitors per BG (calculated by equation (1.3)) to different POI categories during weekends for both income groups. We also overlaid the box plots that the length of the whiskers indicates a maximum of 1.5 times the interquartile range. The patterns in both Figure 2 and Table 3 confirmed the results from Table 2 for lower visitor numbers after the COVID-19 outbreak. Figure 3 provides a visual display of the distributions for the visitor weighted distance traveled for both income groups. Each dot represents a weekly visitor weighted network distance traveled during the weekends for the corresponding category. Visually speaking, the high-income group has more dispersed patterns. The average distance traveled for the high-income group for all categories is 1.64 miles for during COVID-19 and 1.69 miles for pre-COVID-19, while low-income group has an average distance traveled of 1.72 miles during COVID-19 and 1.69 miles pre-COVID-19. "General merchandise stores" and "Supermarkets and other grocery stores" are generally the categories with shorter distances traveled, while visitors travel longer distances for "Drinking places" and "Liquor stores." Only one category (limited-service restaurants) has shown significant decreases for the low-income group. "Supermarkets and other grocery" have not shown significant differences between pre- and during COVID-19 (all $p$-values > 0.05) for all income groups. "Drinking places" have shown disparity between income groups as low-income distance traveled significantly increased

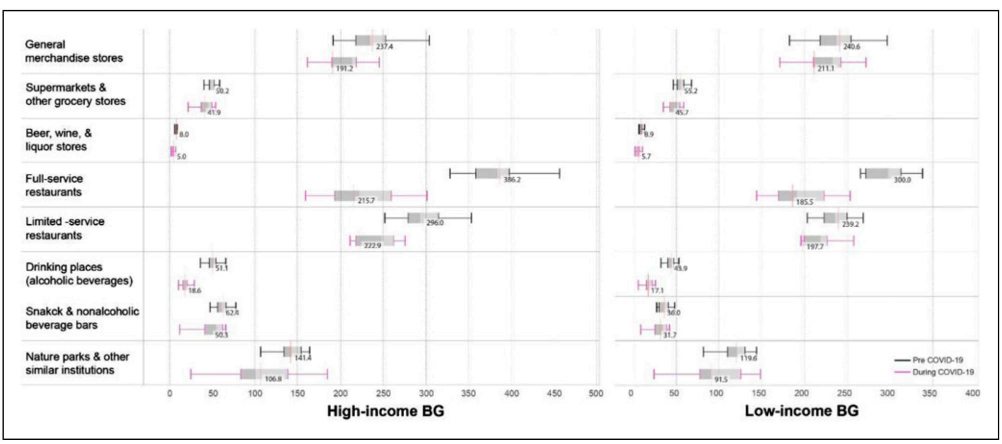


**Figure 2.** POI visitations during pre- versus during COVID-19 periods from the high-income BGs (left) and low-income BGs (right).

**Table 3.** Visitation change and proximity by income.

| COVID effects | High-income BG | | | | | Low-income BG | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Category of POI | During COVID-19* | Pre-COVID-19* | *t* (during-pre) | *p* | Proximity dist. (mi) | During COVID-19* | Pre-COVID-19* | *t* (during-pre) | *p* | Proximity dist. (mi) |
| General merchandise stores | 215.03 (64.68) | 265.25 (31.62) | −3.484 | 0.001 | 1.51 | 179.33 (48.98) | 202.09 (30.69) | −1.946 | 0.058 | 1.09 |
| Supermarkets and other grocery stores[a] | 46.29 (14.16) | 55.51 (5.15) | −3.086 | 0.003 | 1.61 | 39.72 (10.4) | 47.56 (4.81) | −3.426 | 0.001 | 1.08 |
| Beer, wine, and liquor stores | 5.56 (2) | 8.83 (1.88) | −5.773 | 0.000 | 2.30 | 4.89 (2.01) | 7.85 (1.47) | −5.835 | 0.000 | 1.80 |
| Full-service restaurants | 236.52 (68.79) | 418.15 (35.8) | −11.667 | 0.000 | 1.13 | 156.62 (44.9) | 253.02 (29.74) | −8.821 | 0.000 | 0.75 |
| Limited-service restaurants | 245.03 (67.63) | 321.46 (28.28) | −5.235 | 0.000 | 1.18 | 166.81 (45.87) | 201.73 (23.86) | −3.364 | 0.002 | 0.90 |
| Drinking places (alcoholic beverages) | 20.18 (7.7) | 55.36 (7.54) | −15.758 | 0.000 | 1.62 | 14.81 (5.4) | 37.44 (5.26) | −14.486 | 0.000 | 1.48 |
| Snack and nonalcoholic beverage bars | 53.63 (16.27) | 65.82 (9.15) | −3.242 | 0.002 | 1.55 | 26.45 (8.17) | 30.14 (5.72) | −1.815 | 0.076 | 1.55 |
| Nature, parks, and other similar institutions | 116.54 (44.06) | 152.57 (18.03) | −3.801 | 0.000 | 0.94 | 77.78 (30.96) | 102.74 (12.89) | −3.735 | 0.001 | 0.74 |

*Weekly visitors per block group.
[a]except convenience stores.

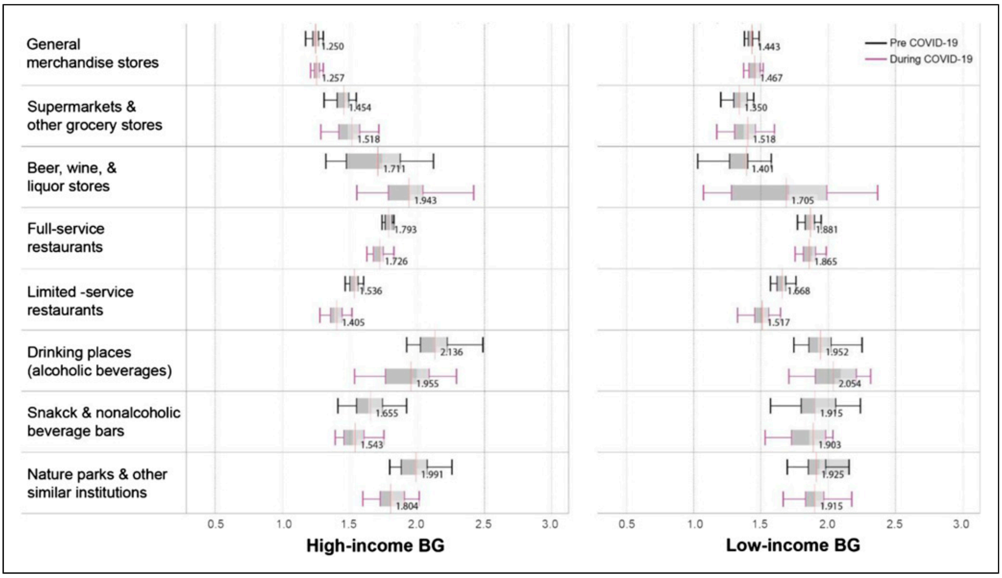


**Figure 3.** Visualization of distance-traveled distributions (high-income BGs left, low-income BGs right).

(T-stats 2.103, *p*-value 0.04) while high-income groups significantly decreased (T-stats −3.5, *p*-value < 0.001).

## Discussion

Although the lockdowns and capacity/gathering restrictions due to COVID-19 were lifted, its direct and indirect impact on our daily living is still apparent (Caroppo et al., 2021; Kumari et al., 2020; Park et al., 2021). Technological advances allowed various alternative forms of working, learning, and living possible through remote working, hybrid teaching/learning, and telemedicine (Shah et al., 2020; Triyason et al., 2020). However, relatively few studies have explored the effects of the COVID-19 pandemic on non-work activities. By using the case of El Paso, Texas, this is one of the first studies that investigated how COVID-19 changed travel patterns related non-work destinations. Our results offered new insights into the changes that COVID-19 brought to the travel patterns of the populations in low- versus high-income neighborhoods. Further, we considered major destinations essential to everyday living such as grocery stores, restaurants, and general merchandise as well as those that support leisure time activities (e.g. nature, parks, sports clubs) important to keep physical and mental health of the populations, especially during the pandemics like COVID-19.

Overall negative effects of COVID-19 on non-work activities are evident as all POI categories showed decreases in visitations during the pandemic (Table 3). After the COVID-19 outbreak, most businesses have undertaken a digital transformation to keep up with heightened safety protocols and changed consumer preferences. As consumers opt for the online option and make larger orders, we might see less frequent visitations to the retail stores and service destinations. Speed and convenience advantage of curbside pickups and home deliveries are found to remain popular and have the potential to thrive beyond the COVID-19 pandemic (Morgan, 2020). Especially for retail, more purchasing time will spend at homes and cars instead of strolling the aisles and choosing products in stores. This may lead to less traveling and reduced physical activities in people's daily routine, although the extent of such effects needs to be seen in future studies.

Regarding the distance traveled to POIs, visitors traveled shorter distances to most the destinations (4 out of 8 POI categories, Table 4). Both the use of and the average travel distance to eating (e.g. full-service restaurants and limited-service restaurants) and drinking places (e.g. beverages, snack, and nonalcoholic) and outdoor physical and social activity places (e.g. parks) had decreased significantly during the COVID-19 pandemic. It seems that visitors choose more local places closer to their homes for these destinations that often involve social interactions. Shopping and food-related service destinations, including general merchandise stores, supermarkets, liquor stores, did not show significantly changes in the distance traveled during the COVID-19 pandemic. Each store has different delivery service policies and customers' preference of the delivery service also differs by various demographic and socioeconomic factors. However, those living near shopping and grocery stores may be more likely to use these delivery services (Grashuis et al., 2020; Chenarides et al., 2021), which may reduce the number of visitors who live close to the shopping and grocery stores and even lead to increase the average distance traveled for these merchandise stores during the COVID-19 pandemic (1.35 miles to 1.37 miles, $p < 0.02$) and supermarkets (1.4 miles to 1.44 miles, $p = 0.08$). The distance traveled to liquor stores has also significantly increased from 1.55 miles pre-COVID-19 pandemic to 1.81 miles during COVID-19 ($p < 0.001$). The recent liquor shortage during COVID-19 (Hernandez, 2021) may have an effect since consumers have to look for other stores further away if nearby stores have limited choices or supplies.

We also found that the COVID-19 pandemic had differently influenced non-work activities between high- and low-income BGs. Most of the patterns of decreasing visitation after the COVID-19 pandemic were similar between high- and low-income BGs, but total visitations of some places decreased more significantly in high-income BGs after the COVID-19 outbreak, compared to the low-income BGs. For example, the decrease in the use of general merchandise stores was significant only in high-income BGs (Δ mean Change: −50.22 visitors per BG, $p < 0.001$ in high-income BGs; Δ mean Change: −22.76 visitors per BG, $p = 0.058$ in low-income BGs). This pattern may be a result of those with high-income and high educational attainment being more aware and accepting of new technology, including online food delivery ordering (Gavilan et al., 2021; Zanetta et al., 2021). Another reason may be that the supplemental nutrition assistance program (SNAP) for low-income households can only be used with in-store visits (National Conference of State Legislature, 2019), requiring the SNAT users to physically visit the stores.

In terms of the distance traveled, those in high-income versus low-income BGs were traveling similar distances before the COVD-19 pandemic (H: 1.69 miles and L: 1.69 miles). However, high-income BGs have decreased their distances traveled to POIs (1.69 mi to 1.64 mi) while low-income BG increased (1.69 miles to 1.72 miles). From Table 3, most places (8 out of 9 POI categories) were further from high-income BGs than from low-income BGs (1.48 miles vs. 1.17 miles), likely because of the tendency that high-income residents tend to live in suburban communities that are predominantly residential, compared to low-income residents more commonly finding their residences in mixed-use areas near downtown and commercial properties (Parker et al., 2018). The strong trend of local consumption (a likely byproduct of working from home) may lead to shorter post-COVID outbreak distances traveled to POIs in high-income BGs. As the travel demand shifts to areas closer to high-income BGs, its business implications and impacts on social segregation and suburbanization need to be further examined in future studies. Moreover, it is worth noting that we see a clear difference in drinking places as visitors in high-income BGs travel shorter distances (post-COVID outbreak decrease of 0.19 miles) while low-income counterparts travel longer distances (post-COVID outbreak increase of 0.1 miles). Since alcohol consumption is responsible for many health and safety consequences (Collins, 2016), future studies may investigate how the change of travel patterns found in this study may affect drinking behaviors and associated risks.

**Table 4.** Distance-traveled comparison between pre- and during COVID-19 by income.

| COVID effects | High-income BG | | | | Low-income BG | | | |
|---|---|---|---|---|---|---|---|---|
| Category of POI | During COVID-19* | Pre-COVID-19* | *t* (during-pre) | *p* | During COVID-19* | Pre-COVID-19* | *t* (during-pre) | *p* |
| General merchandise stores | 1.26 (0.03) | 1.25 (0.03) | 0.773 | 0.444 | 1.47 (0.05) | 1.44 (0.03) | 2.216 | 0.032 |
| Supermarkets and other grocery stores[a] | 1.52 (0.16) | 1.45 (0.06) | 1.829 | 0.074 | 1.37 (0.09) | 1.35 (0.07) | 0.806 | 0.424 |
| Beer, wine, and liquor stores | 1.94 (0.38) | 1.71 (0.23) | 2.576 | 0.013 | 1.7 (0.46) | 1.4 (0.28) | 2.708 | 0.010 |
| Full-service restaurants | 1.73 (0.08) | 1.79 (0.03) | −4.187 | 0.000 | 1.87 (0.09) | 1.88 (0.04) | −0.784 | 0.437 |
| Limited-service restaurants | 1.4 (0.08) | 1.54 (0.04) | −7.634 | 0.000 | 1.52 (0.09) | 1.67 (0.05) | −7.337 | 0.000 |
| Drinking places (alcoholic beverages) | 1.95 (0.21) | 2.14 (0.14) | −3.504 | 0.001 | 2.05 (0.23) | 1.95 (0.13) | 2.103 | 0.041 |
| Snack and nonalcoholic beverage bars | 1.54 (0.12) | 1.65 (0.15) | −2.735 | 0.009 | 1.9 (0.27) | 1.92 (0.19) | −0.270 | 0.788 |
| Nature, parks, and other similar institutions | 1.8 (0.13) | 1.99 (0.13) | −4.961 | 0.000 | 1.91 (0.13) | 1.92 (0.12) | −0.239 | 0.812 |

**Mean of distance traveled.
[a]except convenience stores.

## Limitations and future directions

Several limitations of this study should be acknowledged. We relied on the limited information provided by SafeGraph data and descriptive analysis. SafeGraph data are somewhat limited in representing low-income populations or children who often have limited access to smartphones with GPS, and in the coverage of POIs of small size (Wang et al., 2021). Since SafeGraph data is only provided with aggregated geographical data at the Census BG level, we were unable to consider any individual health and behavior outcomes. Since this study aimed to explore the changes in the general travel patterns in relation to the COVID-19 pandemic, further research is needed to identify the multi-level factors that influence this causal relationship. Another limitation is that we only considered the limited study periods with two 5-month periods before and during COVID-19, and therefore we were unable to assess more completed trends about pre- vs post-COVID-19 changes. However, we used this timeframe to control for the impact of the strict lockdown policy and the short-term surges due to the reopening of the shops immediately after such restrictions. We also mitigated the effects of commuting and work-related activities, which are subject to many other non-environmental confounders that are not of interest to this study, by only including weekend travel activities. Although commonly used in previous studies (DeCoster et al., 2011), our median split method may have BGs of small household income differences ($147 in this case) be classified to different categories. This method can only show general differences between higher vs lower-income groups and could not compare differences of income levels for detailed quantile clusters (e.g. 20% vs 80%). Future research could use regression modeling analysis to offer more detailed analysis on income disparities. There will also be opportunities to test how each policy intervention can influence mobility change and how and to what extent the travel patterns have been changed between weekdays and weekends.

## Policy implication

This study has several implications for policy and interventions in urban planning, transportation, and public health. First, our finding provides evidence of the COVID-19 effects on daily lifestyle even after the initial COVID-19 restrictions were removed. Due to the remote work arrangement by many companies and job loss due to the pandemic, changes in the work-related travel patterns have already been reported. This study provided a comprehensive study on non–work-related destinations and their categorical differences, including grocery shopping, dining, retail shopping, and visiting outdoor physical/social activity places. These non-work destinations and amenities are great benefit to people's well-beings and qualities of lives (Orsega-Smith et al., 2004; Thompson et al., 2011). They play an important role in supporting basic needs such as food intake, social interaction, physical activities, and shopping goods. They are also often small businesses and services that support large amount of local job positions and spending. Urban planners and city managers should not only be aware of the possible impact of future pandemic (e.g., like COVID-19) on work-related travels but also behavior changes of non-work activities. Equitable access should be considered to a variety of non-work amenities for everyone that can support daily utilitarian and recreational needs. It can lead to improving people's coping capability to pandemics like this in the future, by helping to reduce the negative impact of social isolation while also increasing access to non-work destinations. Second, the COVID-19 pandemic may exacerbate the environmental inequalities about non-work destinations by the neighborhood socioeconomic status. Given our findings, low-income residents may be less likely to have reduced visitations and short distances. Compared to high-income residents, low-income residents tend to have greater needs for safe and affordable transportation options, and a compact and walkable urban environment would be advantageous to support their daily travel to non-work destinations during the future contagious pandemic like COVID-19.

## Conclusion

Using the city of El Paso, Texas, as the study site, this study provides a comparison of the travel patterns for different non-work destinations before and during COVID-19 (but after the travel restrictions). By utilizing a large smartphone mobility dataset from SafeGraph, we aggregated measures to estimate travel distances and visitations at the Census BG level to different POI categories such as restaurants, supermarkets, drinking places, and parks. We also evaluated the differences between low- and high-income BGs on those travel patterns. In summary, visitations had a more significant decrease after the COVID-19 outbreak. Travel distances decreased for most POI categories, except for shopping and food-related categories. High-income BGs were more likely to travel shorter distances for non-work activities compared to low-income BGs. Our results presented a comprehensive picture of the changes in travel patterns for non-work destinations after the COVID-19 outbreak and provided insights into future urban mobilities in the post-COVID-19 era. The COVID-19 pandemic exacerbates environmental inequalities by neighborhood socioeconomic status. We think safe and affordable transportation options and compact and walkable urban developments would be imperative to mitigate the negative impact of COVID-19 and similar pandemics or disasters in the future.

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### References

Adams C (2021) *TIMELINE: How Coronavirus in Texas Unfolded Since First Case One Year Ago*. Available at: https://www.kxan.com/news/coronavirus/365-days-of-covid-how-the-coronavirus-intexas-unfolded-one-year-after-the-first-case/

Ashby NJ (2020) Impact of the COVID-19 pandemic on unhealthy eating in populations with obesity. *Obesity* 28(10): 1802–1805.

Beck MJ and Hensher DA (2020) Insights into the impact of COVID-19 on household travel and activities in Australia–The early days under restrictions. *Transport Policy* 96: 76–93.

Bourdas DI and Zacharakis ED (2020) Evolution of changes in physical activity over lockdown time: physical activity datasets of four independent adult sample groups corresponding to each of the last four of the six COVID-19 lockdown weeks in Greece. *Data in Brief* 32: 106301.

Bureau of Labor Statistics (2021) *Consumer Expenditures in 2020*. Available at: https://www.bls.gov/opub/reports/consumer-expenditures/2020/home.htm

Caroppo E, Mazza M, Sannella A, et al. (2021) Will nothing be the same again?: changes in lifestyle during COVID-19 pandemic and consequences on mental health. *International Journal of Environmental Research and Public Health* 18(16): 8433.

Chang S, Pierson E, Koh PW, et al. (2021) Mobility network models of COVID-19 explain inequities and inform reopening. *Nature* 589(7840): 82–87.

Chenarides L, Grebitus C, Lusk JL, et al. (2021) Food consumption behavior during the COVID-19 pandemic. *Agribusiness* 37(1): 44–81.

Chiou L and Tucker C (2020) Social distancing, internet access and inequality. Reportno. Report Number|, Date. Place Published|: Institution|.

City of El Paso (2020) *Health Orders*. Available at: https://www.epstrong.org/health-orders.php

Collins SE (2016) Associations between socioeconomic factors and alcohol outcomes. *Alcohol Research: Current Reviews* 38(1): 83–94.

DeCoster J, Gallucci M and Iselin A-MR (2011) Best practices for using median splits, artificial categorization, and their continuous alternatives. DOI: 10.5127_jep.008310.

Ding D, Cheng M, del Pozo Cruz B, et al. (2021) How COVID-19 lockdown and reopening affected daily steps: evidence based on 164, 630 person-days of prospectively collected data from Shanghai, China. *International Journal of Behavioral Nutrition and Physical Activity* 18(1): 1–10.

Dueñas M, Campi M and Olmos LE (2021) Changes in mobility and socioeconomic conditions during the COVID-19 outbreak. *Humanities and Social Sciences Communications* 8(1): 1–10.

Federal Highway Administration. (2017). *2017 National Household Travel Survey*, U.S. Department of Transportation, Washington, DC. Available online: https://nhts.ornl.gov.

Fernandez J, Song Y, Padua M, et al. (2022) A framework for urban parks: using social media data to assess bryant park, New York. *Landscape Journal* 41: 15–29.

Fraiberger SP, Astudillo P, Candeago L, et al. (2020) Uncovering socioeconomic gaps in mobility reduction during the COVID-19 pandemic using location data. arXiv preprint arXiv:2006.15195.

Gao S, Li M, Liang Y, et al. (2019) Predicting the spatiotemporal legality of on-street parking using open data and machine learning. *Annals of GIS* 25(4): 299–312.

Gavilan D, Balderas-Cejudo A, Fernández-Lores S, et al. (2021) Innovation in online food delivery: learnings from COVID-19. *International Journal of Gastronomy and Food Science* 24: 100330.

Google LLC (2022) *Google COVID-19 Community Mobility Reports*. Available at: https://www.google.com/covid19/mobility/ (accessed 3 Jan, 2022).

Grashuis J, Skevas T and Segovia MS (2020) Grocery shopping preferences during the COVID-19 pandemic. *Sustainability* 12(13): 5369.

Grengs J (2010) Job accessibility and the modal mismatch in Detroit. *Journal of Transport Geography* 18(1): 42–54.

Hernandez J (2021) Why liquor shortages caused by the COVID-19 pandemic persist in some states.

Hicks JL, Althoff T, Sosic R, et al. (2019) Best practices for analyzing large-scale health data from wearables and smartphone apps. *NPJ Digital Medicine* 2(1): 1–12.

Huang X, Li Z, Jiang Y, et al. (2020) Twitter reveals human mobility dynamics during the COVID-19 pandemic. *PLoS One* 15(11): e0241957.

Huang X, Li Z, Jiang Y, et al. (2021) The characteristics of multi-source mobility datasets and how they reveal the luxury nature of social distancing in the U.S. during the COVID-19 pandemic. DOI: 10.1080/17538947.2021.1886358.

Jay J, Bor J, Nsoesie EO, et al. (2020) Neighbourhood income and physical distancing during the COVID-19 pandemic in the United States. *Nature Human Behaviour* 4(12): 1294–1302.

Kumari A, Ranjan P, Vikram NK, et al. (2020) A short questionnaire to assess changes in lifestyle-related behaviour during COVID 19 pandemic. *Diabetes & Metabolic Syndrome: Clinical Research & Reviews* 14(6): 1697–1701.

Lawson CT (2018) 2018 national household travel survey workshop. *Transportation Research Circular*. (E-C238).

Lio CF, Cheong HH, Lei CI, et al. (2021) Effectiveness of personal protective health behaviour against COVID-19. *BMC Public Health* 21(1): 1–10.

Maciag M (2017) *Vehicle Ownership in U.S. Cities Data and Map*. Available at: https://www.governing.com/archive/car-ownership-numbers-of-vehicles-by-city-map.html

McCahill C (2018) Non-work accessibility and related outcomes. *Research in Transportation Business & Management* 29: 26–36.

Morgan B (2020) *3 Lasting Changes to Grocery Shopping after Covid-19*. Available at: https://www.forbes.com/sites/blakemorgan/2020/12/14/3-lasting-changes-to-grocery-shopping-after-covid-19/?sh=713000af54e7

National Conference of State Legislature (2019) Restrictions on use of public assistance electronic benefit transfer (EBT) cards.

Orsega-Smith E, Mowen AJ, Payne LL, et al. (2004) The interaction of stress and park use on psycho-physiological health in older adults. *Journal of Leisure Research* 36(2): 232–256.

Park KH, Kim AR, Yang MA, et al. (2021) Impact of the COVID-19 pandemic on the lifestyle, mental health, and quality of life of adults in South Korea. *PLos One* 16(2): e0247970.

Parker K, Horowitz J, Brown A, et al. (2018) What unites and divides urban, suburban and rural communities.

Prestby T, App J, Kang Y, et al. (2020) Understanding neighborhood isolation through spatial interaction network analysis using location big data. *Environment and Planning A: Economy and Space* 52(6): 1027–1031.

Reuscher T, Hwang H-L and Lim H (2017) Travel patterns and characteristics of low-income subpopulation in New York state. Reportno. Report Number|, Date. Place Published|: Institution|.

Ruiz-Euler A, Privitera F, Giuffrida D, et al. (2020) Mobility patterns and income distribution in times of crisis: US urban centers during the COVID-19 pandemic. Available at SSRN 3572324.

SafeGraph (2019) *What about Bias in the SafeGraph Dataset?* Available at: https://www.safegraph.com/blog/what-about-bias-in-the-safegraph-dataset

SafeGraph (2020) Places Schema.

Safegraph (2022) *Neighborhood Patterns | SafeGraph Docs*. Available at: https://docs.safegraph.com/docs/neighborhood-patterns

Saha J, Barman B and Chouhan P (2020) Lockdown for COVID-19 and its impact on community mobility in India: An analysis of the COVID-19 Community Mobility Reports, 2020. *Children and Youth Services Review* 116: 105160.

Saif MA, Zefreh MM and Torok A (2019) Public transport accessibility: a literature review. *Periodica Polytechnica Transportation Engineering* 47(1): 36–43.

Sehra ST, George M, Wiebe DJ, et al. (2020) Cell phone activity in categories of places and associations with growth in cases of COVID-19 in the US. *JAMA Internal Medicine* 180(12): 1614–1620.

Shah S, Diwan S, Kohan L, et al. (2020) The technological impact of COVID-19 on the future of education and health care delivery. *Pain Physician* 23: S367–S380.

Snedecor GW and Cochran WG (1989) *Statistical Methods*. 8th edition. Ames, Iowa 1191: Iowa State University Press.

Song Y, Newman G, Huang X, et al. (2022a) Factors influencing long-term city park visitations for mid-sized US cities: A big data study using smartphone user mobility. *Sustainable Cities and Society* 80: 103815.

Song Y, Ning H, Ye X, et al. (2022b) Analyze the usage of urban greenways through social media images and computer vision. *Environment and Planning B: Urban Analytics and City Science* 49: 1682–1696.

Thompson JL, Bentley G, Davis M, et al. (2011) Food shopping habits, physical activity and health-related indicators among adults aged≥ 70 years. *Public Health Nutrition* 14(9): 1640–1649.

Triyason T, Tassanaviboon A and Kanthamanon P (2020) Hybrid classroom: designing for the new normal after COVID-19 pandemic. In: Proceedings of the 11th International conference on advances in information technology, Bangkok Thailand, 1–3 July, 2020, pp. 1–8.

U.S. Census Bureau (2020) *Quick Facts: El Paso City, Texas*. Available at: https://www.census.gov/quickfacts/fact/table/elpasocitytexas/PST045221

United States (2020) *Proclamation on Declaring a National Emergency Concerning the Novel Coronavirus Disease (COVID-19) Outbreak*. Available at: https://trumpwhitehouse.archives.gov/presidential-actions/proclamation-declaring-nationalemergency-concerning-novel-coronavirus-disease-covid-19-outbreak/

Van Dijcke D and Wright AL (2020) Using mobile device traces to improve near-real time data collection during the george floyd protests. Available at SSRN 3621731.

van Wee B and Witlox F (2021) COVID-19 and its long-term effects on activity participation and travel behaviour: a multiperspective view. *Journal of Transport Geography* 95: 103144.

Wang J, McDonald N, Cochran AL, et al. (2021) Health care visits during the COVID-19 pandemic: a spatial and temporal analysis of mobile device data. *Health & Place* 72: 102679.

Ye X, Wang S, Lu Z, et al. (2021) Towards an AI-driven framework for multi-scale urban flood resilience planning and design. *Computational Urban Science* 1(1): 1–12.

Yeganeh AJ, Hall RP, Pearce AR, et al. (2018) A social equity analysis of the US public transportation system based on job accessibility. *Journal of Transport and Land Use* 11(1): 1039–1056.

Zanetta LDA, Hakim MP, Gastaldi GB, et al. (2021) The use of food delivery apps during the COVID-19 pandemic in Brazil: the role of solidarity, perceived risk, and regional aspects. *Food Research International* 149: 110671.

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Sungmin Lee explores the relationship between the built environment and public health. His primary research interests are neighborhood environments, environmental justice, and health disparity. Particularly, he explores the environmental health of vulnerable populations and disadvantaged neighborhoods. He pursues the question of how outdoor environments and green spaces could promote people's health and safety.

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