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Human mobility data demonstrates increase in park visitation since start of COVID-19 pandemic in Buffalo, New York

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ABSTRACT

Background: The COVID-19 pandemic highlighted the importance of urban parks to provide safe places to visit and recreate. Recent research has suggested that park visitation over this time may not have occurred equitably, which may exacerbate existing health disparities. However, usual methods of estimating park visitation are labor intensive, requiring better solutions.. The objective of this study was to assess how park visitation changed in Buffalo, New York after the start of the COVID-19 pandemic utilizing human mobility data.

Methods: Monthly mobile phone location data from January 2018 through October of 2021 from residents of Buffalo were analyzed to estimate total park visits for each census tract. A generalized linear mixed effect model was utilized to examine if selected factors affected park visitation. Factors examined included demographic, health, park, and crime data at the census tract level.

Results: Across 587,487 park visits that were captured in the 79 census tracts, park visitation increased by 25% since March 2020. In our regression model, having cancer and currently smoking had negative effects on park visitation. The start of the COVID-19 pandemic positively affected park visitation. Season (of the year), was the other statistically significant variable that affected park visitation.

Conclusions: Anonymous mobile phone data demonstrated that park visitation has increased by 25% since the beginning of the pandemic when we looked at census tract level data. While some data limitations must be addressed, mobile phone data is a novel method that can be used to understand behavioral and public health trends.

1. Introduction

The COVID-19 pandemic has dramatically affected the health and behaviors of people across the globe, with most changes negatively affecting health behaviors and outcomes. Initial lockdowns closed many public and community spaces until knowledge about the virus and its transmission led to recommendations to limit indoor exposure risk to mitigate spread (Geng et al., 2021; Razani et al., 2020). Subsequently, outdoor areas became safer places to congregate and recreate (Larson et al., 2021; Bulfone et al., 2021; Rowe et al., 2021). The pandemic has highlighted the importance of urban park use to promote active lifestyles, improve stress and emotional well-being given, improving both physical and mental well-being (Larson et al., 2021; Nita et al., 2021; Jay et al., 2021; Sallis et al., 2021). Similarly, active transportation including walking and biking to and from parks in neighborhood settings also can provide healthy ways to increase physical activity.

Recent research has demonstrated that park use increased during the pandemic (Geng et al., 2021; Jay et al., 2021), while others have not (Larson et al., 2021), leading to inconsistencies in the literature, and perhaps suggesting contextual factors that affected park use across the U.S. Large scale systemic park observations tend to require a large amount of time or resources (Nita et al., 2021). One reasonable solution has been to utilize human mobility datasets to estimate park use with cell phones as the data source (Larson et al., 2021; Jay et al., 2021). Human mobility data has been used in several research disciplines, including public health, as it can signify patterns of human behaviors as well as socioeconomic indicators (Kang et al., 2020). The few studies utilizing mobile phone data across the U.S. demonstrated that racial and socioeconomic differences were seen in park use during the pandemic (Larson et al., 2021; Jay et al., 2021), reinforcing concerns that the pandemic has exacerbated pre-existing health disparities (Larson et al., 2021; Honey-Roses et al., 2020). This study, therefore, contributes to the broader theoretical literature on social equity, specifically on park use and equity, and can provide additional evidence for understanding the effects of the pandemic on park use by different communities. (Vaughan et al., Apr 2018; Boone et al., 2009).

Buffalo is the second largest city in New York State, with a population of approximately 256,000 (Erie County Community Health

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Assessment, 2019). Considered a “rust belt” city, it has significant areas of segregation and poverty. Rates of cardiovascular disease are much higher than the national average and are worse in underserved areas in Buffalo. Notably, the East and West sides of Buffalo have the highest rates of segregation, poverty, and poor health outcomes (Erie County Community Health Assessment, 2019). Given these persistent inequities, we wondered if park use would differ between different communities in Buffalo, which could worsen the entrenched and notable health related disparities. One large urban park system in Buffalo reported a 40 % increase in park use during the pandemic, although it is not clear how they estimated park visitation (Watkins, 2021). Also, there was no comment on which populations or communities were utilizing the park system more often in the report leading our team to assume this had not been examined.

In this research, we set out to explore how the COVID-19 pandemic has changed park visitation in Buffalo, while looking at the impact of health, demographics, crime, and park-related variables. While human mobility data has been used in other fields of business and research, we believe it can also be employed to better understand health behaviors important to population health. The ability to look at longitudinal data on a neighborhood level will allow us to compare population groups within one city. This novel method could be utilized for the study of many health behaviors and be utilized across population and public health practice across the world. The primary aim of our study was to characterize how urban park visitation has changed in Buffalo since the start of the pandemic. Our secondary aim was to analyze which potential factors affected park visitation utilizing several pre-existing datasets.

2. Methods

2.1. Data sources

Census tract data was chosen as the unit of analysis because this was the most granular level of data possible for all data sets utilized. Four datasets were used in this study to look at multiple factors that could affect park visitation. The primary data source was monthly park visits extracted from the anonymized mobile phone location data provided by the company SafeGraph. The anonymized data of SafeGraph was collected from 45 million mobile devices, mostly smartphones (Fox, 2019), which represent about 10 % of the total US population. The locations were collected and aggregated from apps installed on smartphones, such as weather apps or other location-based service apps (e.g., apps for searching nearby restaurants). These mobile phone location data were further overlaid with about 3.6 million points of interest (POIs) representing different places in the US, and parks are included in these POIs. Visits to a POI are detected when a mobile phone location falls within the boundary of the POI (e.g., when the GPS points of a mobile phone fall within a park).

SafeGraph also used several additional techniques (e.g., spatial clustering and machine learning) and information (e.g., the opening hours of a POI) to further increase the accuracy of the identified POI visits. More technical details can be found in the reports released by SafeGraph (Determining points of interest visits from location data: a technical guide to visit attribution., 2021). The data are anonymized and are not associated with any personal identifying information. In addition, the exact GPS trajectory points of mobile phones are not provided to further protect privacy, and the data are in the form of aggregated POI visits and general home neighborhoods of the POI visitors (inferred based on the nighttime locations of the mobile devices during the previous six weeks). The general home neighborhoods were provided in both census block group and census tract levels.

Monthly park visits were derived from the anonymized mobile phone location data using the following steps. First, parks were selected from the many POIs using its corresponding North American Industry Classification System Code (NAICS) in the data, which is “Nature Parks or Similar Places” (712190). A spatial filter was created based on the city boundary of Buffalo which removed parks outside of city limits. In total, there were 204 parks in Buffalo included for analysis.

Second, visits to these parks each month were extracted from the anonymized mobile phone location data and connected to the home census tracts of the POI visitors. Here, the focus of the data was reversed from individual parks to individual census tracts to measure how frequently the residents of a specific census tract visited all parks in Buffalo. Specifically, unique visits to different parks coming from the same census tracts were aggregated. Then, the total number of visits was divided by the total number of mobile devices residing in the same census tracts to obtain the park visit ratio. This was a necessary variable to create to account for population density differences, since census tracts with higher populations are likely to have higher numbers of visits.The time range of monthly SafeGraph data was from January 2018 to October of 2021.

Demographic and socioeconomic data was extracted from the American Community Survey (ACS) data from the US Census Bureau. Demographics chosen for our model from the ACS data include: age, disability status, educational attainment, median household income, % with health insurance, race: black, white or other, % Hispanic, % with a car, and place of birth. CDC PLACES data from 2020 was utilized to look at health behaviors and outcomes estimates of each census tract. This dataset relies on the Behavioral Risk Factor Surveillance System survey that the CDC performs annually in adults $\geq$ 18 years. This data set includes a total of 36 measures, with categories including health behaviors, prevention, health status, and health outcomes. We chose to narrow our focus and selected six of these variables that we thought could affect park visitation for our study: coronary heart disease, cancer, diabetes, obesity, no leisure time physical activity, and currently smoking. Lastly, Open Data Buffalo is a city-maintained database that includes the Crime Incidents dataset, which utilizes preliminary police reports of crime reported to the Buffalo Police Department. From this dataset, we created a two-part crime variable based the count of total incidents in each census tract from January 2018 through April of 2021. The variable was modeled after previous definitions and research (Marquet 2020) to sort Part 1 and Part 2 offenses Type 1 offenses include: homicide, rape, robbery, aggravated assault, burglary, larceny, motor vehicle theft, arson, and human trafficking. All other reported crimes fall under Part 2 offenses.

2.2. Data analysis

Seventy-nine census tracts were included in this analysis and the park visit rate was calculated for each month from January 2018 through October of 2021. We applied a linear mixed effects model with random intercept to examine the association between park visitation ratios and COVID-19 status and seasonal effect. Mixed effects model allows us to account for correlation among outcomes within census tracts (parks) over multiple days of observation while controlling for day-level covariates. Two main effects in the model were “COVID-19 Pandemic” and “Season”. “COVID-19 Pandemic” was defined as the start of the COVID-19 pandemic, selected as the month of March 2020, as that is when shut-downs and drastic changes began to occur in Buffalo. “Season” represents the four seasons (Spring, Summer, Fall, and Winter) of the year. Model covariates included the prevalence of selected health measures mentioned before, employment status, disability status, college status, household income, crime, insurance status, race variables (while, black, and other), and car ownership. Covariates are measured by percentage, e.g. college status is the percentage of those who attended some college in certain census tracts.

. To visually assess the park visitation over the entire study period, locally weighted scatterplot smoothing (LOESS) curve was plotted using the nine Buffalo Common Council Districts. To formally evaluate the park visitation changes over time, a linear mixed effect regression (LMER) model with random intercept term for each city council district and fixed factorial effect term for COVID-19 status (non COVID-19 vs.

COVID-19) is considered. Statistical analysis was performed in statistical software R, using the packages lme4, lmerTest, and ggplot2.

3. Results

A total of 587,487 park visits were captured from people in the 79 census tracts included in the sample. On average, 18,757 phones were included in each monthly dataset. Total park visitation in Buffalo increased by 25 % between March 2020 and October 2021. Table 1 has a summary of demographic attributes for city residents, divided by the 9 common city council districts. The N in each represents the number of census tracts that are located in each district.

Fig. 1 shows the map of the districts within the city. Fig. 2 displays park visitation for all districts in Buffalo, with each district represented by a different color. The coefficient associated with COVID-19 is positive and statistically significant (Table S3 in Supplemental Files), which indicates all city council districts showed an increase in park visitation after the start of the COVID-19 pandemic.

In our regression model, season (of the year) and the start of the COVID-19 pandemic were found to be statistically significant variables that affected park visitation. After the start of the COVID-19 pandemic, the park visitation ratio increased 0.25 compared with normal period, meaning park visitation increased by 25 %. There were significant increases in park visitation depending on the season seen. When it was spring, summer, or fall, the park visitation ratio increased 0.11, 0.28, and 0.16, respectively, compared to when it was winter.

In addition, the prevalence of cancer and smoking were found to significantly decrease park visitation. When the prevalence of cancer in the population increased by 10 %, the park visitation ratio was decreased by 1 %; and when the prevalence of currently smoking population increased by 10 %, the park visitation ratio was decreased by 0.4 %. No other related factors (e.g., park, crime, race, disability, or other health variables) statistically affected visitation (Table 2).

4. Discussion

This study utilized anonymous human mobility data from mobile phones and found that park visitation in Buffalo, NY increased by 25 % in city residents from March of 2020, which we defined as the beginning of the COVID-19 pandemic. The start of the pandemic and season were statistically significant variables that affected park visitation. Two health measures also affected park visitation, having cancer and currently smoking, which both were shown to decrease park visitation. Currently smoking and having cancer have both been shown to decrease physical fitness and physical activity, so our findings likely reflect this. (Jeon et al., 2021; Romero et al., Dec 2018) However, there were no other significant differences in park visitation seen between demographic, health, crime, or park variables. While we are not sure why other health conditions like having obesity or diabetes did not affect park visitation, we did find it interesting that no leisure time physical activity was also not significant. This might mean an already active subset of people because even more active rather than sedentary people becoming newly active during the early pandemic time.

Our study is consistent with several other recent studies that suggest park visitation increased during the pandemic in various locations throughout the U.S. and abroad (Geng et al., 2021; Robinson et al., 2021; Grima et al., 2020; Alizadehtazi et al., 2020; Eyler et al., 2019). Surveys in the U.S. suggest that respondents increased their park

Table 1
Demographics of the nine Buffalo Common Council Districts in 2020.

	Buffalo Common Council Districts								
	DELAWARE (N = 7)	ELLICOTT (N = 13)	FILLMORE (N = 10)	LOVEJOY (N = 7)	MASTEN (N = 8)	NIAGARA (N = 8)	NORTH (N = 8)	SOUTH (N = 9)	UNIVERSITY (N = 8)
Variables	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
White (%)	77.81 (12.45)	32.19 (27.80)	42.00 (28.91)	56.17 (39.14)	10.61 (13.95)	59.48 (20.41)	56.60 (12.38)	89.07 (5.92)	30.46 (28.94)
Black (%)	16.55 (10.98)	60.84 (33.50)	45.80 (29.24)	39.81 (39.36)	87.51 (16.04)	18.63 (9.71)	21.71 (9.93)	6.61 (4.00)	60.40 (34.39)
Other (%)	8.66 (4.45)	10.71 (10.66)	15.76 (14.50)	6.73 (3.13)	4.48 (4.40)	27.01 (17.04)	30.09 (8.68)	8.13 (5.13)	12.18 (11.92)
Hispanic ethnicity (%)	8.79 (3.56)	11.72 (17.28)	12.09 (11.39)	7.46 (3.79)	1.80 (1.95)	19.09 (13.70)	21.55 (7.93)	11.44 (8.96)	5.70 (4.89)
Coronary Heart Disease (%)	5.21 (0.64)	8.55 (2.19)	9.55 (2.09)	8.67 (1.12)	8.95 (1.53)	6.22 (1.98)	8.34 (1.30)	7.14 (1.37)	5.61 (2.28)
Cancer (%)	6.27 (0.89)	6.82 (1.55)	5.92 (0.63)	6.67 (1.10)	6.51 (1.18)	5.04 (0.57)	5.99 (0.49)	6.84 (0.54)	4.83 (1.85)
Diabetic (%)	8.54 (1.02)	17.69 (6.07)	18.60 (4.50)	15.29 (3.29)	20.35 (3.55)	11.35 (3.97)	13.86 (2.19)	10.81 (2.17)	12.72 (6.27)
No leisure-time physical activity (%)	19.14 (2.70)	32.18 (8.76)	37.23 (7.05)	33.34 (5.07)	35.34 (3.85)	27.64 (9.29)	33.30 (5.26)	26.09 (4.78)	27.56 (8.86)
Current smoker (%)	15.49 (2.81)	22.05 (5.38)	29.51 (5.84)	27.03 (3.77)	23.95 (2.48)	21.51 (5.88)	27.41 (4.21)	22.58 (4.25)	20.64 (6.26)
Obesity (%)	28.70 (2.61)	39.67 (7.56)	42.86 (5.11)	39.29 (6.38)	43.96 (4.32)	33.24 (5.29)	37.62 (3.31)	32.60 (3.40)	35.90 (10.83)
Unemployed (%)	2.89 (1.80)	5.73 (4.01)	7.83 (3.10)	6.49 (2.73)	8.28 (3.23)	3.13 (1.65)	3.50 (1.54)	5.35 (1.84)	6.11 (4.40)
Disabled (%)	10.32 (2.63)	21.15 (7.51)	20.01 (5.61)	18.29 (2.00)	18.67 (4.01)	13.67 (4.64)	16.48 (3.93)	15.05 (4.61)	13.03 (4.84)
Some college completed (%)	10.32 (2.63)	21.15 (7.51)	20.01 (5.61)	18.29 (2.00)	18.67 (4.01)	13.67 (4.64)	16.48 (3.93)	15.05 (4.61)	13.03 (4.84)
With health insurance (%)	95.08 (3.11)	94.77 (2.34)	92.69 (1.52)	92.11 (1.42)	93.36 (3.35)	93.58 (2.18)	93.07 (1.58)	94.68 (3.48)	94.27 (3.74)
Own a car (%)	83.17 (10.7)	67.04 (13.7)	60.46 (9.70)	68.64 (9.01)	64.40 (7.78)	71.87 (11.62)	68.10 (6.87)	85.27 (7.61)	73.62 (16.7)
Crime score	101.29 (36.94)	153.69 (63.26)	179.70 (55.11)	184.43 (64.40)	174.25 (96.08)	144.50 (51.16)	187.50 (72.08)	108.22 (69.05)	178.62 (101.86)
Number of parks	3.71 (4.07)	2.92 (3.62)	2.30 (1.95)	1.86 (1.35)	2.62 (2.00)	3.00 (2.20)	2.11 (1.54)	4.56 (1.94)	5.00 (5.40)
Acreage of parks	51.49 (81.24)	12.22 (25.27)	6.54 (7.21)	18.90 (19.45)	11.99 (19.09)	7.57 (14.38)	12.13 (17.53)	84.94 (156.65)	8.79 (11.47)
Median household income ($)	57,757 (19,579)	34,185 (16,176)	23,077 (7,663.8)	30,296 (4,423.8)	26,640 (4,423.8)	38,595 (13,836)	29,940 (12,718)	45,954 (12,992)	34,435 (19,969)

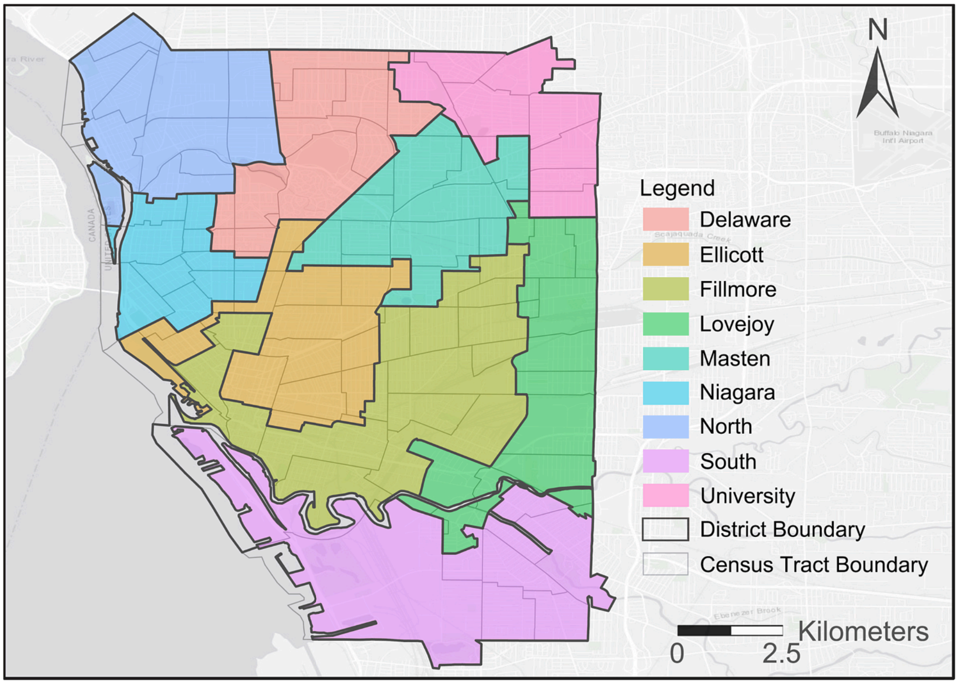

Fig. 1. A map of the Buffalo common council districts and census tracts in 2020.

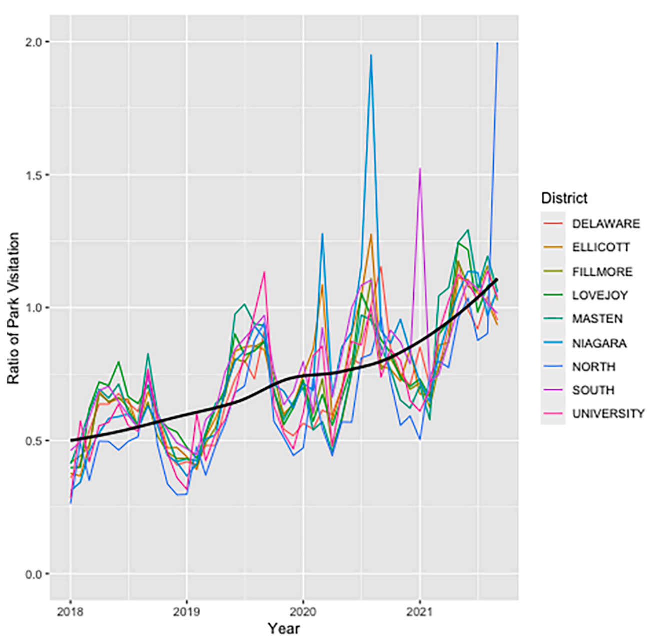

Fig. 2. Park Visitation Ratio for All Buffalo Districts.

Table 2
Park visitation linear mixed effects model.

	Park Visitation Ratio			
Predictors	*Estimates*	*std. Error*	*Statistic*	*p*
Intercept	2.34	0.98	2.39	0.017
COVID-19	0.25	0.01	24.40	<0.001
Season				
Fall	0.16	0.01	11.22	<0.001
Spring	0.11	0.01	7.72	<0.001
Summer	0.28	0.01	19.97	<0.001
Coronary Heart Disease	0.10	0.05	1.90	0.057
Cancer	−0.10	0.04	−2.48	0.013
Diabetes	−0.04	0.03	−1.28	0.199
No leisure time physical activity	0.02	0.02	0.79	0.427
Current smoker	−0.04	0.02	−2.37	0.018
Obesity	0.01	0.02	0.30	0.761
Unemployed	0.13	0.71	0.19	0.850
Disability	−0.09	0.43	−0.20	0.841
Attended college	−0.36	0.32	−1.10	0.271
Median household income	0.02	0.04	0.65	0.513
Crime variable	−0.00	0.00	−1.50	0.134
Have health insurance	−0.69	0.69	−0.99	0.320
White race	−0.38	0.65	−0.58	0.563
Black race	−0.36	0.63	−0.57	0.566
Other race	−0.82	0.60	−1.38	0.166
Own a car	−0.06	0.24	−0.23	0.818
	Random Effects			
σ^2	0.09			
$\tau_{00\ tractfps}$	0.02			
ICC	0.15			
$N_{tractfps}$	78			
Observations	3503			
Marginal R^2 / Conditional R^2	0.234 / 0.349			

visitation over this time, from 69 % reporting visiting more in one study (Grima et al., 2020) and time and length of stay increasing by 40 min a visit and 1 additional day a week (Robinson et al., 2021). A wide variation of increases in park visitation was seen internationally, with rates quoted at 0–50 % in some countries to increased up to over 100 % in certain countries like Canada, Denmark, and the United Kingdom (Geng et al., 2021). While initial visitation to parks dropped in the most immediate months of widespread closure of public spaces, most parks were open in the Summer of 2020 with physical distancing requirements in place (Larson et al., 2021). Those in Buffalo mirrored this trend, where park-goers were encouraged to be used for passive recreation while maintaining social distancing, even closing two large parks to traffic to encourage this in the park system which reporting increased use by 40 % (Watkins, 2021; Buffalo, 2020).

Human mobility was tracked during the pandemic often using anonymized mobile phone location data (Gao et al., 2020; Chang et al., Jan 2021; Grantz et al., 2020), when distancing and shut downs were encouraged, and demonstrated that reductions in mobility was one potential way to reduce COVID-19 cases (Johnson et al., 2021). However, early data clearly demonstrated that the use of parks and other greenspace was associated with a reduction in COVID-19 cases, especially compared to indoor amenities or areas where populations would cluster (Johnson et al., 2021). Another study revealed that 88 % of participants increased their visits and time spent in nature during the pandemic and that those with higher greenness around them predicted high levels of mental wellbeing (Robinson et al., 2021).

Our findings contrast with other studies about park use since the start of the pandemic, where park visits in underserved or minority communities seemed to decline or were less than affluent areas, leading to concerns that the pandemic could widen pre-existing health disparities (Larson et al., 2021; Jay et al., 2021), as public spaces may be the only recreational spaces available to those who are socially disadvantaged (Honey-Roses et al., 2020). Since our study only looked at Buffalo, which has a high level of park access compared to other cities in the U.S., our different outcome may reflect that most people in the city still had access to parks, which would explain our different results. (Master, 2021) The multiple benefits of park use including physical activity, stress reduction and well-being are highly recommended needs for urban residents to remain healthy, especially during pandemic times. (Honey-Roses et al., 2020; Robinson et al., 2021) Environmental justice concerns, like decreased park use, is another way people feel the pandemic might further widen health disparities in minoritized communities. (Larson et al., 2021).

Our use of SafeGraph mobile phone data is critical to this study, however known limitations to this dataset exist. This dataset will only include people with smartphones. This will exclude young children, older adults, and some lower income people (roughly 24 % of those with income below $30,000 do not have smart phone access. (Vogels, 2021) It will also exclude those with location setting turned off to mobile apps. In addition, this type of data does not capture the actual activities of the mobile phone users in the park, and only provides information about park visits. However, even socializing with others or observing nature in a park can lead to health benefits. (Robinson et al., 2021; Swierad and Huang, 2018).

Another limitation of this study is in the use of census tracts as the geographic units for analysis. Since all independent and outcome variables need to be aggregated to census tracts, the obtained variable values are inevitably affected by the boundaries of these geographic units and using a different type of geographic unit (e.g., census block groups) could lead to a different analysis result. This is known as the modifiable area unit problem (MAUP). (Fotheringham, 1991; Nelson, 2017 2017) We used census tracts in this study largely because the CDC PLACES data were aggregated to this level of geographic unit. When more detailed data becomes available, we could conduct further studies using census block groups or other smaller geographic units.

A greater push for understanding and measuring personal behaviors had led to increased interest in the fields of preventive and lifestyle medicine. Traditional ways of measuring park visitation are often expensive or require significant time and labor. (Zhang and vBD, Howe PD, Miller ZD, Smith JW. , 2021; Wood et al., 2013) The SafeGraph dataset allows us to look at many parks, at the same time, longitudinally to understand visitation changes. In Buffalo, we were able to review 204 parks over three years in a short amount of time. Utilizing existing big data to quickly measure and assess behavior change is one step to see change on a population health level. This may help address the call for increased monitoring of physical activity in the U.S. (Sallis and Pate, 2021).

Importantly, anonymized mobile phone location data is a new source of population data that can look at settings for health behaviors as well as other location based public health places of interest or trends including recreation, food, and health care and can reflect on socioeconomic indicators. (Kang et al., 2020) This study only represents one use of this data, which many other researchers may find useful to their work. Existing studies have also used mobile phone location data to study alcohol outlet visiting behaviors, social distancing behaviors, use of health care facilities, and other topics (Wang et al., Nov 2021; Weill et al., 2020; Chang et al., Jan 2022). While our current study was limited to one city in the U.S., our methods of analyzing this data have generalizability to other locations and could be utilized in a similar fashion. In this way, researchers can partner with municipalities, policy makers, community organizations, or businesses to utilize location data to look at health behaviors in their communities in a rapid way to better understand current or trend data.

5. Author Statement

JT: Conceptualization, data curation, writing- original draft preparation. JW: Methodology, visualization, formal analysis, writing-reviewing and editing. RZ: methodology, formal analysis, writing- review and editing. YH: conceptualization, methodology, formal analysis, writing- review and editing.

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CRediT authorship contribution statement

Jill N. Tirabassi: Conceptualization, Funding acquisition, Data curation, Writing – original draft, Writing – review & editing, Visualization, Investigation. **Jia Wang:** Data curation, Writing – original draft, Writing – review & editing, Visualization, Validation, Formal analysis, Methodology. **Ryan Zhenqi Zhou:** Methodology, Formal analysis, Writing – original draft, Writing – review & editing. **Yingjie Hu:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.pmedr.2024.102650.

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