The Effect of Built Environment on Urban Park Visits during the Early Outbreak of COVID-19

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Findings

During the COVID-19 early outbreak, the effects of built environment on individuals' urban park visitation are understudied. We employed structural equation modeling to disentangle such complex relationships and investigate the impacts over time at the census tract level across the 100 largest American cities. The results show that density and design both explain park visitation, while only the dimension of density has major influences on the distance to urban parks.

1. Questions

Urban parks are instrumental to public health. However, the outbreak of the COVID-19 pandemic dramatically changed the public mobility patterns due to the containment measures. Urban residents were, therefore, likely to exhibit different patterns of park visitation due to various built environment factors (Xiong et al. 2020), so that people's mental and physical well-being were at risk during the pandemic (Ding, Li, and Sang 2022; Krendl and Perry 2020). For example, densely populated cities, where people are under higher risk of the detrimental effects of COVID-19 (Cortwright 2020), might see a decrease in large urban park visit (Zhai, Yue, and Deng 2022). Sometimes, urban parks may even serve as transmission hotspots for the virus transmission (Volenec et al. 2021), because pedestrian activity increased in city parks, peri-urban forests, green open spaces, as well as restricted open areas due to different built environment characteristics of the area (Venter et al. 2020). In addition to urban park shutdowns that were posited to reduce the risk, social distancing policies, restrictions on social gatherings, and closure of workspace in urban parks may have also affected park visits (Geng et al. 2021; Fu and Zhai 2021); however, none of these containment measures have been examined yet in the context of urban green space. Hence we seek to answer the following questions: how the neighborhood built environment impacts individuals' urban park visits during the early outbreak of COVID-19, and how the built environment effects change after the declare of containment measures?

2. Methods

The census tract group is used as the spatial unit. The study region has 11,269 census tracts from the 100 largest American cities, spanning the time period between March 16, 2020 and April 20, 2020 on a weekly basis. In order to explore the relationship between the built environment and park visitations systematically, we applied structure equation modeling (SEM) in this work (Figure 1). There are eight latent variables that are the variables of interest in this research. The motive of using SEM is that it allows us to study both the
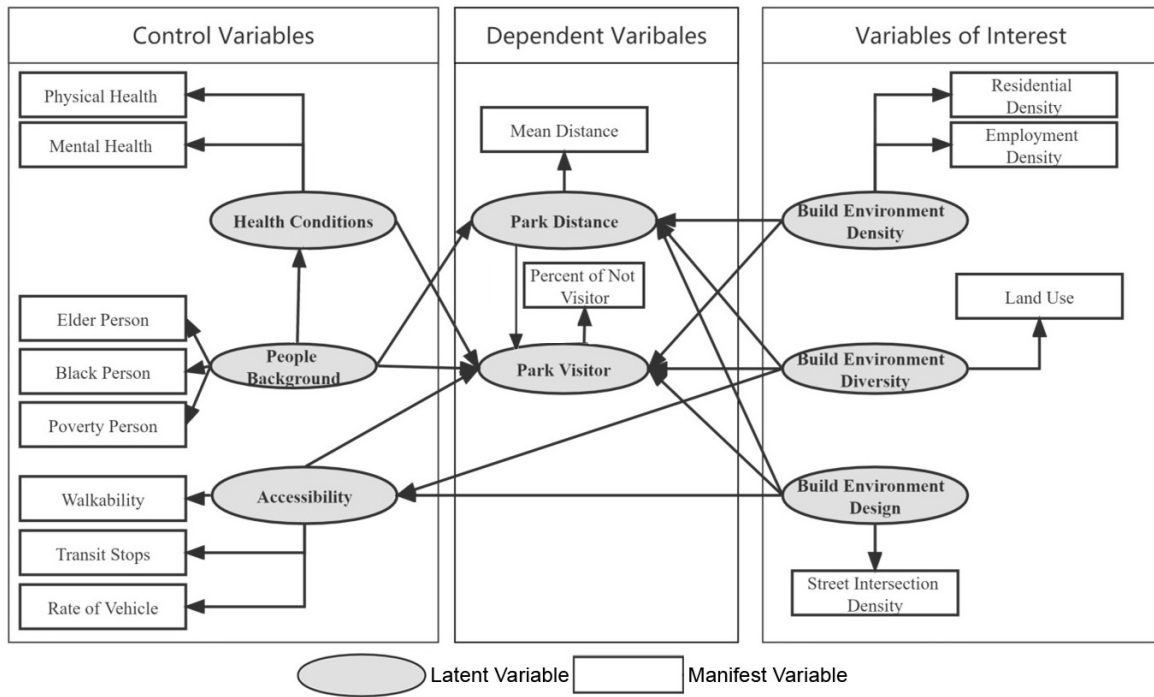
Figure 1. Framework of the structure equation modeling

direct and indirect effects of built environment variables while conventional OLS regressions cannot address such questions. In [Table 1](#), we specify the variables.

Dependent variables. The dependent variables are the distance to the urban parks and the percentage of residents who visit urban green parks, derived from the SafeGraph mobility data. The raw data includes the mobility records of over 40 million users' mobile devices across the United States, revealing the number of weekly trips from each neighborhood to different types of points of interest (Weill et al. 2020; Zhai et al. 2021). Specifically, the variable of distance is calculated by the arithmetic mean distance of mobile devices from each neighborhood to parks. Likewise, the park visit is the percent of mobile devices in a census tract that visited the urban park during a given week. We assume that distance to the park will impact the park visitations since people are less likely to travel to urban parks that are farther away from their homes (Gao, Zhai, and Fu 2023).

Independent variables. Built environment is a multi-dimensional variable resulting from a myriad of spatial variables (Handy et al. 2002). Here, we use density, diversity and design. (1) Density is represented by residential density and employment density at tract level. (2) Land use entropy is used to indicate the diversity of built environment, because it takes into account the purposes for which various buildings are made in an area. Mathematically, the measure was obtained by land use entropy$= \sum_i \frac{P_i * \ln(P_i)}{\ln(i)}$. In the equation, i is the number of land uses included and P_i represents the share of each land use i. We used commercial, official, residential, industrial and other land use types

Table 1. describes variables, data sources and summary statistics (N=11,269)

Variable	Description	Mean	SD	Min	Max
Urban Park[a]					
Distance	The average distance for each community to parks	12.8	28.74	0.01	915.51
Park Visit	Percentage of residents who did not visit urban green parks	0.75	0.33	0	0.99
Socioeconomics[b]					
Elderly People	The rate of elder people	0.12	0.06	0	1
Poverty	The rate of poverty people	0.3	0.28	0	1
Black	The rate of black people	0.21	0.27	0	1
Accessibility[c]					
Transit Stops	The quantity of transit stops in one square mile (2,588,881m^2)	28.64	38.87	0	484.37
Rate of Vehicle	The rate of people who have any vehicle	0.83	0.43	0	1.65
Walkability		13.4	2.91	0	32.6
Health Conditions[d]					
Mental Health	Mental health not good for >=14 days among adults aged >=18 Years	11.75	5.86	0	32.6
Physical Health	Physical health not good for >=14 days among adults aged >=18 Years	11.04	5.64	0	32.4
Built environment-Density[e]					
Residential Density	Gross residential density(house/acre) on unprotected land	13	17.83	0	298.63
Employment Density	Gross employment density(jobs/acre) on unprotected land	12.44	57.37	0	2826.67
Built environment-Diversity					
Land Use Entropy	Calculated by authors	6.72	20.34	0	484.37
Built environment-Design[e]					
Street Intersection Density	Intersection density per square mile	113.26	87.31	0	1422.45

Note: The data sources can be found below

a. SafeGraph COVID-19 Data Consortium (https://www.safegraph.com/)

b. American Community Survey (https://www.census.gov/programs-surveys/acs)

c. Smart Location Database (https://www.epa.gov/smartgrowth/smart-location-mapping)

d. 500 Cities Project (https://www.cdc.gov/places/about/500-cities-2016-2019/index.html)

for this variable. The value ranges are from 1 to 0. A greater land use entropy represents more diverse land use, while a lower value indicates less types of land use. (3) The dimension of design is represented by street intersection density, indicating street design in an urban area.

Control variables. Age and demographic background may partially explain park visitation. We also added accessibility variables, including the numbers of stops per square mile, number of vehicles per family, and walkability. Due to the high correlation between people's mobility and health conditions, variables for mental health and physical health are also considered, respectively.

3. Findings

Our results of the SEM can be found in Tables 2 and 3, regarding the direct effects and indirect effects, respectively. Note that since we have weekly trips from SafeGraph, we ran the SEM over the weeks between March 16th, 2020 and April 20th, 2020 to examine the effects over time.

Table 2. Effects of all variables on park visitations

	03/16/2020		03/23/2020		03/30/2020		04/06/2020		04/13/2020		04/20/2020	
	Coeff	p value	Coeff	p value	Coeff	p value	Coeff	p value	Coeff	p value	Coeff	p value
Total Effects												
Health Conditions	0.225***	0	0.12***	0.002	0.069	0.077	0.158***	0	0.206***	0	0.104***	0.005
Socioeconomics	0.303*	0.078	0.171	0.103	0.092	0.178	0.298**	0.018	0.275*	0.04	0.156	0.673
Density	-1.28**	0.018	-1.321***	0	-1.56***	0	-1.988***	0	-1.311***	0	-2.23***	0
Design	-0.003**	0.038	0.013**	0.018	0.031*	0.078	0.046*	0.086	0.001**	0.011	0.052**	0.012
Diversity	-0.101	0.123	-0.107	0.232	-0.132	0.223	-0.132	0.182	-0.124	0.132	-0.134	0.232
Accessibility	0.049***	0.001	0.081***	0	0.084***	0	0.124***	0	0.079***	0	0.121***	0
Direct Effects												
Health Conditions	0.225***	0	0.12***	0.002	0.069	0.077	0.158***	0	0.206***	0	0.104***	0.005
Socioeconomics	-0.059**	0.012	-0.016	0.507	-0.015	0.515	0.053**	0.028	-0.044*	0.07	-0.005	0.838
Density	-0.645**	0.016	-0.668***	0	-0.799***	0	-1.007***	0	-0.676***	0	-1.124***	0
Design	-0.061**	0.041	-0.052	0.027	-0.039	0.137	-0.041	0.146	-0.057	0.013	-0.04	0.203
Diversity	-0.097***	0	-0.102***	0	-0.126***	0	-0.123***	0	-0.122***	0	-0.126***	0
Accessibility	0.049***	0.001	0.081***	0	0.084***	0	0.124***	0	0.079***	0	0.121***	0
Indirect Effects												
Health Conditions	-	-	-	-	-	-	-	-	-	-	-	-
Socioeconomics	0.362***	0	0.187***	0.002	0.107*	0.078	0.245***	0	0.319***	0	0.161***	0.005
Density	-0.635**	0.019	-0.653***	0	-0.761***	0	-0.981***	0	-0.635***	0	-1.106***	0
Design	0.058	0.034	0.065***	0.001	0.07***	0.002	0.087***	0	0.057***	0.003	0.092***	0.001
Diversity	-0.004	0.519	-0.005	0.379	-0.006	0.421	-0.009	0.349	-0.002	0.679	-0.008	0.454
Accessibility	-	-	-	-	-	-	-	-	-	-	-	-

*p<0.1; ** p<0.05; ***p<0.01

Table 3. Total effects of all variables on travel distance to urban parks

	03/16/2020		03/23/2020		03/30/2020		04/06/2020		04/13/2020		04/20/2020	
	Coeff	p value	Coeff	p value	Coeff	p value	Coeff	p value	Coeff	p value	Coeff	p value
Health Conditions	-0.073	0.144	-0.147***	0	-0.091	0.022	-0.104***	0.008	-0.102***	0.009	-0.132***	0.001
Socioeconomics	0.018	0.446	0.085***	0.001	0.051	0.035	0.006	0.823	0.03	0.228	0.056**	0.02
Density	-0.969***	0.005	-0.854***	0	-0.778***	0	-0.602***	0	-0.493***	0.001	-0.989***	0
Design	0.07*	0.07	0.059	0.227	0.033	0.206	0.021	0.331	0.018	0.387	0.048	0.189
Diversity	0.039***	0.004	-0.01	0.432	-0.014	0.254	0.004	0.612	-0.015	0.204	0.002	0.891
Accessibility	0.049***	0.001	0.081***	0	0.084***	0	0.124***	0	0.079***	0	0.121***	0

*p<0.1; ** p<0.05; ***p<0.01

Note: Based on Figure 1, there are no mediating effects of all the variables on distance to urban parks. That is to say, the total effects equal direct effects.

(1) **Density**. The total effects of neighborhood density on park visitations, including direct and indirect effects, are significant and negative after the nationwide emergency announcement of COVID-19 (Mar 13th, 2020). This suggests that higher neighborhood density is associated with a lower rate of urban park visits during the pandemic. This could be due to the fact that higher population or employment density results in more green spaces accessible within the neighborhood, reducing the need to visit urban public parks, which could potentially expose residents to the risk of infection. This explanation also applies to the negative effect of density on the distance to urban parks, which exhibits a similar pattern as the effects on park visitations.

(2) **Design**. The built environment design has significant positive effects on park visitations after March 16th, 2020. This could be because individuals prefer to engage in physical activities around their homes rather than in public parks during the pandemic, as noted by Carr, Dunsiger, and Marcus (2010). Moreover, higher levels of intersection densities and street connectivity are known to contribute to increased physical activity, promoting walkability and public health enhancement (Molaei, Tang, and Hardie 2021). Interestingly, the direct effects of built environment design are not statistically significant for either urban park visitations or travel distance to urban parks, over time. However, the indirect effects are significant after the declaration of State of Emergency for COVID-19. On the other hand, the total effects of distance to parks are not significant after March 16th, 2020.

(3) **Diversity**. The overall impact of diversity on park visitation is not statistically significant; however, the direct effect of diversity is worth noting. This could be due to research indicating that mixed land use can enhance walkability in a community, potentially reducing residents' inclination to visit urban parks (Mavoa et al. 2018). On the other hand, diversity does not significantly affect the distance to parks post-March 16th, 2020, implying that the effects of land use diversity are negligible during the pandemic. This could be attributed to the fact that many individuals are now working remotely, making them more likely to visit parks in close proximity to their homes or within their neighborhoods.

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