Association of city-level walkability, accessibility to biking and public transportation and socio-economic features with COVID-19 infection in Massachusetts, USA: An ecological study

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Abstract

With people restricted to their residences, neighbourhood characteristics may affect behaviour and risk of coronavirus disease 2019 (COVID-19) infection. We aimed to analyse whether neighbourhoods with higher walkability, public transit, biking services and higher socio-economic status were associated with lower COVID-19 infection during the peak of the COVID-19 pandemic in Massachusetts. We used Walk Score®, Bike Score®, and Transit Score® indices to assess the walkability and transportation of 72 cities in Massachusetts, USA based on availability of data and collected the total COVID-19 case numbers of each city up to 10 April 2021. We used univariate and multivariate linear models to analyse the effects of these scores on COVID-19 cases per 100,000 in each city, adjusting for demographic covariates and all covariates, respectively. In the 72 cities studied, the average Walk Score, Transit Score and Bike Score was 48.7, 36.5 and 44.1, respectively, with a total of 426,182 COVID-19 cases. Higher Walk Score, Transit Score, and Bike Score rankings were negatively associated with COVID-19 cases per 100,000 persons (<0.05). Cities with a higher proportion of Hispanic population and a lower median household income were associated with more COVID-19 cases per 100,000 ($P<0.05$). Higher Walk Score, Transit Score and Bike Score were shown to be protective against COVID-19 transmission, while socio-demographic factors were associated with COVID-19 infection. Understanding the complex relationship of how the structure of the urban environment may constrain commuting patterns for residents and essential workers during COVID-19 would offer potential insights on future pandemic preparedness and response.

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See online Appendix for additional material.

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Introduction

The main non-pharmacologic intervention for the coronavirus disease 2019 (COVID-19) during the first wave was social distancing policy, and in Massachusetts State regulators instituted a stay-at-home on March 24, 2020 (Commonwealth of Massachusetts, 2020a). Consequently, the built environment at the neighbourhood-level could become important environmental determinants of health for residents. For example, during the implementation of stay-at-home orders, people are generally limited to their residences except for necessities of daily living, when they are more exposed to the effect of the built environment of their surroundings. Additionally, with social distancing limitations on public transportation during the peak of the COVID-19 pandemic, the mobility patterns of individuals may be significantly limited by how 'walkable' or 'bikeable' their neighbourhood may be.

Walkable neighbourhoods are a strong predictor of higher physical activity, lower body mass index (BMI), and active travel (Smith *et al*., 2008; Pucher *et al*., 2010; Hirsch *et al*., 2013). The Walk Score (www.walkscore.com) is a novel and validated index (with regularly updated walkability data) for distances to amenities, including parks and stores (Duncan, 2013), with a higher Walk Score indicating higher proximity and convenience. Transit Score (https://www.walkscore.com/transit-score-methodology.shtml) measures how well an area is served by public transit, and Bike Score (https://www.walkscore.com/bike-score-methodology.shtml) whether a location is good for biking. Some studies showing higher Transit Score and Bike Score were associated with increased transit ridership and cycling (Hirsch *et al*., 2013; Winters *et al*., 2016).

Given that more walkable neighbourhoods are negatively associated with chronic diseases (Chiu *et al*., 2016; Méline *et al*., 2017) as well as infectious diseases (Adlakha and Sallis, 2020; Nieman and Wentz, 2019), we hypothesized that walkability and accessibility to biking and public transportation would be associated with communicable disease transmission during the first wave of the COVID-19 pandemic. Especially as people were on lockdown due to stay-at-home orders and ban on travel, built environmental factors could potentially influence community-level transmission of COVID-19. Therefore, using granular municipal-level data on the built environment and COVID-19 cases, we sought to understand the relationship between the built environment and COVID-19 case growth. Our study had two objectives. First, we aimed to determine whether Walk Score®, Bike Score® and Transit Score® are associated with cases of COVID-19 per 100,000 persons. Second, we aimed to determine whether COVID-19 infections are related to socio-economic factors (SES), particularly racial and ethnic disparities, to better validate recent findings on the differences (Gold *et al*., 2020; Muñoz-Price *et al*., 2020; Zelner *et al*., 2021). Investigation of SES would be essential, because they could either confound or alternatively be mediators for the effects of the built environment and COVID-19 outcomes.

Materials and methods

COVID-19 prevalence

We obtained COVID-19 confirmed case counts for 72 cities from the Massachusetts Department of Public Health (DPH), Bureau of Infectious Disease and Laboratory Sciences (Commonwealth of Massachusetts, 2020a). Since 22 April 2020, the Massachusetts Department of Public Health has reported weekly updates of COVID-19 confirmed cases for every city or town. These data are derived from the DPH epidemiological surveillance database. We collected the cumulative confirmed cases for the 72 cities up to 10 April 2021. We calculated COVID-19 rates as cases per 100,000 persons by dividing total confirmed cases of each city by city-level population size estimated by the US Census.

Walk Score®, Transit Score® and Bike Score® ratings

Walk Score®, Transit Score® and Bike Score® ratings measure the walkability, access to public transit and bike infrastructure of addresses and cities using a patented system (Walk Score advisory board, 2020). Walk Score analyses hundreds of walking routes to nearby amenities, and points are awarded for each location based on the distance to different kinds of amenities. Data sources include the US Census 'Google', 'Factual', 'Great Schools', 'Open Street Map', 'Localeze' and places added by the Walk Score user community. Transit Score ranking is calculated by assessing the frequency, type of route and distance to the nearest stop on the route. Transit Score works in any city with available public transit data in the General Transit Feed Specification (GTFS) format published by its transit agencies. Bike Score index measures whether a place is good for biking based on four equally weighted components: bike lanes; hills; bike commuting mode share and destinations; and road connectivity. Data sources include the United States Geological Survey (USGS), Open Street Map and the US Census. The three scores are all normalized to a score between 0-100 using scores from cities that have good transit accessibility or bike infrastructure as a canonical 100 score. Walk Score Inc. also ranks cities and neighbourhoods by calculating the three scores of approximately every city block, a grid of latitude and longitude points spaced roughly 500 feet apart, weighted by population density. We obtained the Walk Score, Transit Score, and Bike Score rankings for 72 cities in Massachusetts (www.walkscore.com/MA) based on data availability of Walk Score as of Bike Score. Figure 1 shows Walk Scores for the 72 cities in MA. We categorized Walk Score and Bike Score indices into three tertiles. Because only 51 municipalities have Transit Score data, we grouped all 72 cities into three groups: cities without Transit Score data, cities at the lower 50% and cities at the upper 50%. We also divided them into several groups for Walk Score, Transit Score, and Bike Score rankings: 0-49 as 'car-dependent,' 50-69 as 'somewhat walkable,' 70-100 as 'very walkable' for Walk Score; cities without Transit Score as 'missing,' 0-49 as 'some transit,' 50-100 as 'good transit' for Transit Score; 0-49 as 'somewhat bikeable,' 50-69 as 'bikeable,' and 70-100 as 'very bikeable' for Bike Score.

Neighbourhood socio-economic predictors

Race distribution and household income measured at the city-level were the socio-economic predictors in our study. We obtained the data from American Community Survey (ACS) 2019 5-year estimate (US Census Bureau, 2019). We coded race distribution and household income and grouped the cities into tertiles based on percentage of Hispanic population, percentage of black and median household income.

Neighbourhood covariates

The covariates were the measured populations at the city-level. The population density was defined as the ratio of the population estimated by the US Census to the area of cities in square miles provided by the Bureau of Geographic Information (2020) in the form of interactive maps and associated descriptive information (MassGIS). We used ACS 2019 5-year estimate on age distribution, car ownership and unemployment rate (US Census Bureau, 2019) for this study. Percentage of population over 65 years of age, percentage of households without cars, and unemployment rate of every city were included as covariates. We calculated the hospital bed number in every city using the list of health care facilities licensed or certified by the Division of Health Care Facility Licensure and Certification (2020). We included the number of hospital beds per 1000 as a covariate, defined as the ratio of hospital bed number to the population at city-level multiplied by 1000.

Statistical analysis

First, we calculated the mean, standard deviation (SD) and median (25th percentile, 75th percentile) of the demographic and social-economic characteristics for different tertiles and groups of Walk Score, Transit Score and Bike Score. We categorized cities into tertiles of the three Scores, household income, and race/ethnicity. We analysed the correlation of COVID-19 cases per 100,000, Walk Score, Transit Score, Bike Score and other characteristics. We used univariate and multivariate linear models for our regression analysis, using Walk Score, Transit Score, and Bike Score indices as continuous independent variables and their tertiles and groups as categorical independent variables. We also used tertiles of race and income variables as categorical independent variables. The outcomes were COVID-19 cases per 100,000 persons. The models were population-weighted, adjusted for demographic covariates (log-transformed population density, percentage of pop-

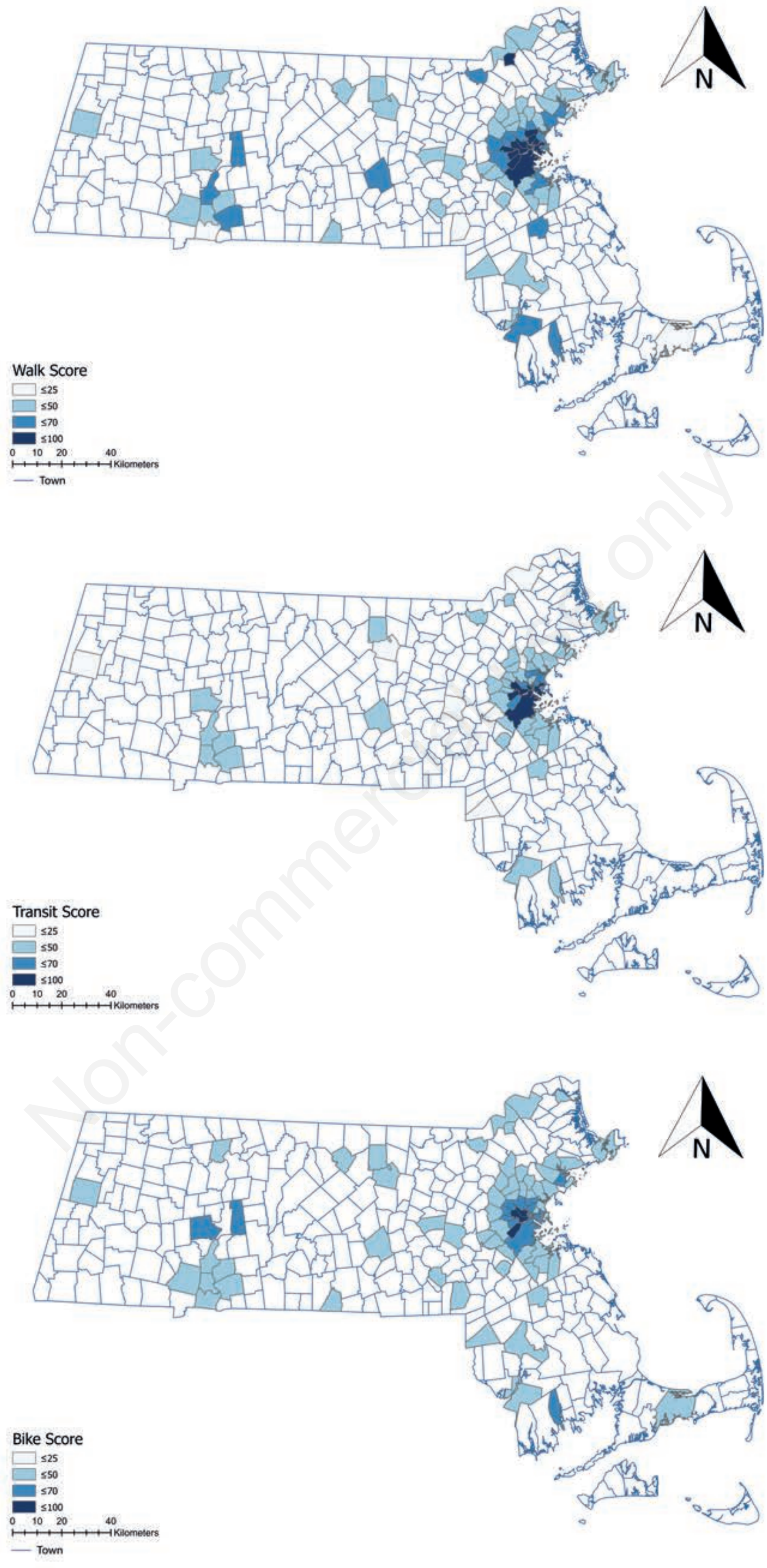

Figure 1. City level Walk, Bike and Transit Score in 72 Massachusetts cities.

ulation over 65 years of age, and tertiles of race variables) and all covariates (log-transformed population density, percentage of population over 65, percentage of households without cars, unemployment rate, and hospital beds per 1000 people) separately. We performed all analyses in SAS Studio University Edition. A workflow chart is provided in Figure 2.

Results

Descriptive statistics

We analysed 72 cities or towns in Massachusetts with a population range of 16,426 (Southbridge) to 700,047 (Boston), covering 60.6% of the total population in the state. Spearman's correlations between Walk Score, Transit Score, and Bike Score were strong: 0.814 between Walk Score and Transit Score (P<0.001), 0.762 between Walk Score and Bike Score (P<0.001), and 0.75 between Transit Score and Bike Score (P<0.001) (Table S1 in Appendix). Cities with higher Walk Score, Transit Score and Bike Score tended to have higher population, higher population density, more Hispanic and black residents, more households without cars, lower household income, higher unemployment rate and fewer people over 65 years of age (Tables 1 and 2). Places with higher COVID-19 incidence rates tended to be negatively associated with median household income, percentage of people over 65 and Bike Score (Table S1 in Appendix).

Relationship of the three scores with COVID-19 cases per 100,000

In the fully adjusted model, the continuous variables for walkability, transit and biking services were negatively associated with COVID-19 cases rate (Tables 3 and 4). Every 10 points increase in Walk Score was associated with a decrease of 1089.4 (95% CI: –2240.8 to 61.9, P=0.0632) cases per 100,000 persons. Every 10 points increase in Transit Score was associated with a decrease of 1915.7 (95% CI: –3329.4 to –502.1, P=0.0092) cases per 100,000 persons, and for Bike Score, the number was 2,059.2 (95% CI: –2882.2 to –1236.3, P<0.001) cases per 100,000 persons.

Relationship of SES Factors with COVID-19 cases per 100,000

In our fully adjusted model, cities with a higher proportion of Hispanic population were associated with more COVID-19 cases per 100,000 (Table S2 in Appendix). Compared to the first tertile, cities at the third tertile of Hispanic proportion had 3278.4 (95% CI: 709.7 to 5847.1, P=0.0133) more cases per 100,000 with Walk Score in the regression model. Higher household income group was also associated with a lower COVID-19 rate (P<0.001).

Discussion

The geospatial pattern of the spread of COVID-19 is similar to

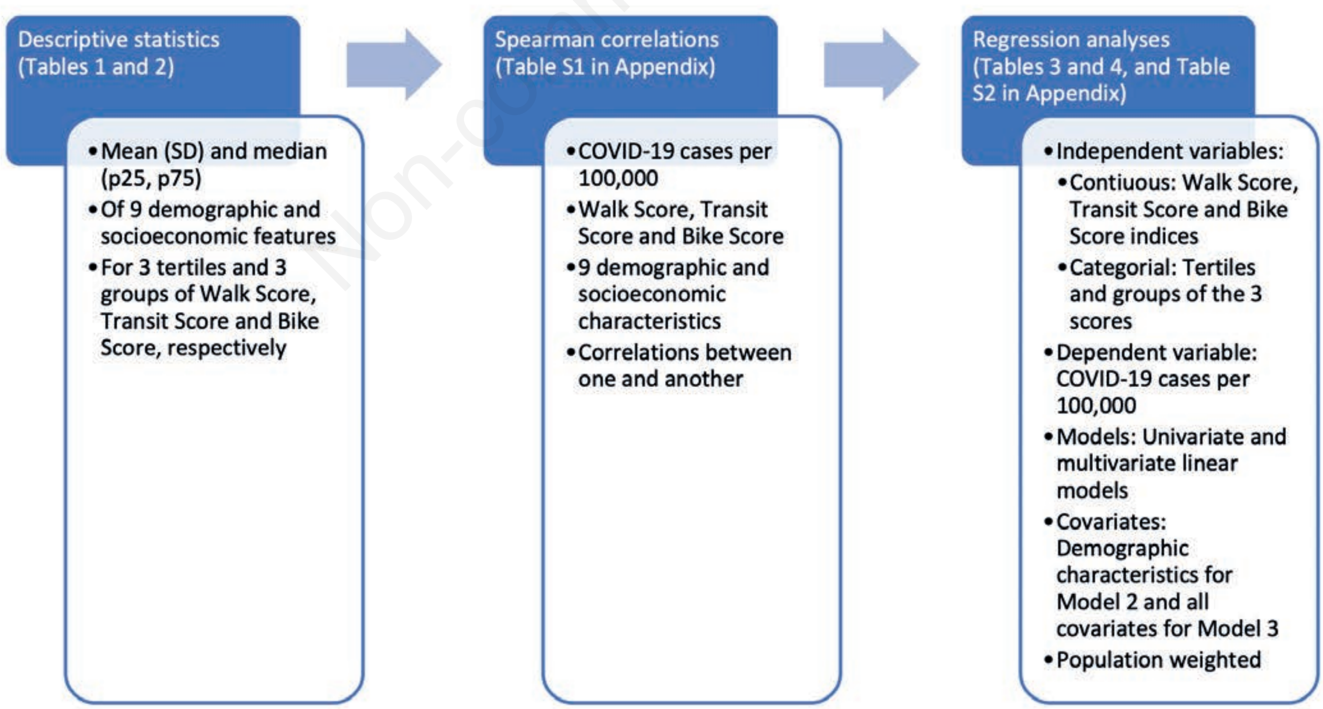

Figure 2. Workflow chart of statistical analysis.

other infectious diseases. Loth *et al*. (2011) found that 'commercial poultry population,' two indicators of market locations and transport, 'human settlements' and 'road length' were associated with an elevated risk of highly pathogenic avian influenza. Lai *et al*. (2013) examined the association between tuberculosis prevalence and floor levels using sky view factor and found people living on lower floors were associated with higher TB prevalence in taller buildings. Ngwa *et al*. (2016) found significant associations between cholera transmission and the presence of major waterbody or highway, modified climate subzones.

Table 1. Characteristics of cities by tertiles of Walk Score, Transit Score and Bike Score.

Characteristic		Overall pop (no.)	Pop density (persons/mile^2)	Hispanic pop (%)	Black pop (%)	Cars (%)	Income (USD)	Work (%)	Beds/1000	Pop >65 (%)
Total (n=72)										
	Mean	57687.1	4396.6	13.3	5.9	11.7	86084.7	4.7	3.4	16.3
	SD	81286.7	4176.1	15.0	7.8	7.3	34411.4	1.7	3.3	3.4
	Median	40272.5	2723.1	8.7	3.5	10.3	79074.0	4.4	2.7	16.4
	P25	28164.0	1772.4	4.5	2.1	6.4	60147.0	3.5	0.4	14.2
	P75	58408.5	5312.7	17.0	5.8	16.0	101326.0	5.8	5.9	18.2
Walk Score										
Tertile 1 (n=24)	Mean	34453.7	1925.2	6.5	5.2	6.9	101265	4.4	3.3	17.8
	SD	10840.9	808.1	6.3	8.8	2.9	43953.1	1.2	3.5	2.7
	Median	32113.0	2002.4	5.1	2.8	6.6	84528.5	4.1	2.6	17.2
	P25	27579.0	1207.2	2.6	1.8	4.8	68403.0	3.5	0.2	15.9
	P75	42186.0	2475.1	8.9	5.0	7.8	129326.5	5.7	5.4	19.4
Tertile 2 (n=25)	Mean	41089.4	2514.6	12.8	5.0	9.5	81206.1	4.8	3.5	17.2
	SD	21532.0	1227.6	11.8	8.3	4.2	25434.6	1.9	2.9	3.5
	Median	39736.0	2366.6	8.7	2.9	9.3	80943.0	4.4	2.7	18.0
	P25	26993.0	1765.1	5.0	1.9	6.4	58469.0	3.4	1.0	14.2
	P75	52906.0	3148.5	15.1	5.0	10.8	95964.0	5.2	5.8	20.2
Tertile 3 (n=23)	Mean	99971.8	9021.0	21.0	7.7	19.2	75547.1	5.0	3.5	13.9
	SD	133882.2	4573.0	20.5	6.1	7.4	26487.9	1.8	3.6	2.8
	Median	60984.0	8142.9	12.4	5.4	18.5	68808.0	5.0	2.3	14.4
	P25	43252.0	5441.4	6.8	3.0	11.9	56181.0	3.5	0.0	11.2
	P75	95239	12031.4	28.3	10.8	23.9	101103.0	5.9	6.2	16.5
Transit Score										
Missing (n=21)	Mean	30860.5	2127.6	8.6	2.6	7.9	94104.8	4.5	2.9	17.4
	SD	12097.1	1533.3	8.5	1.8	3.6	41038.1	1.7	3.6	3.6
	Median	28696.0	2001.0	5.4	2.3	7.3	80943.0	3.9	0.6	16.8
	P25	20610.0	1230.5	3.0	1.6	4.9	6894.0	3.5	0.0	15.1
	P75	39736.0	2330.9	9.5	3.3	10.7	118721.0	5.0	5.8	20.9
Group 1 (n=27)	Mean	45955.8	2657.3	10.1	5.6	9.0	84607.4	4.6	3.9	17.5
	SD	32642.6	1352.6	7.4	8.0	4.4	30425.7	1.4	2.9	2.8
	Median	40304.0	2579.6	8.6	4.0	7.8	82510.0	4.4	3.0	17.3
	P25	28516.0	1447.6	3.8	2.1	6.3	66522.0	3.5	1.1	15.7
	P75	44789.0	3494.1	16.1	5.8	10.8	96522.0	5.6	6.1	19.3
Group 2 (n=24)	Mean	94358.2	8338.5	21.2	9.2	18.1	80729.0	5.1	3.4	14.0
	SD	129782.4	5025.7	21.8	9.6	8.2	32453.8	2.0	3.5	2.9
	Median	60082.0	7889.1	10.8	5.4	18.0	68545.0	5.1	2.7	14.3
	P25	42772.5	4770.0	5.7	3.0	11.2	56491.5	3.4	0.3	11.4
	P75	93975.0	11396.9	31.0	12.9	23	105054.5	6.0	5.7	16.7
Bike Score										
Tertile 1 (n=26)	Mean	35797.6	1888.7	9.6	3.3	7.7	90921.7	4.6	3.3	17.7
	SD	12644.9	773.0	9.3	2.0	3.3	34985.2	1.5	3.3	3.3
	Median	32113.0	1899.5	5.7	3.0	7.1	82529.0	4.1	2.5	17.2
	P25	27586.0	1184.0	3.1	2.0	5.4	68944.0	3.5	0.6	15.1
	P75	41606.0	2488.0	9.9	4.5	10.0	100757.0	5.2	5.0	20.2
Tertile 2 (n=21)	Mean	43167.8	3146.3	10.2	5.2	9.6	87648.9	4.4	3.7	17.7
	SD	37603.5	1805.3	11.6	9.2	5.1	37638.0	1.3	3.4	2.3
	Median	29306.0	2728.3	6.8	2.8	8.8	82510.0	4.9	2.7	17.7
	P25	23223.0	1922.6	3.3	1.6	6.4	53225.0	3.4	0.4	15.9
	P75	42766.0	3582.4	10.6	4.1	11.4	101549.0	5.6	7.5	19.6
Tertile 3 (n=25)	Mean	92648.5	8055.0	19.8	9.3	17.6	79740.2	5.2	3.4	13.7
	SD	127379.7	5111.9	19.9	9.4	8.2	31276.1	2.1	3.3	2.9
	Median	60984.0	7660.8	11.1	5.6	17.9	66522.0	4.7	3.1	13.8
	P25	43252.0	4660.0	7.5	3.1	10.8	56878.0	3.5	0.2	11.2
	P75	93743.0	10762.4	20.8	10.8	21.8	101103.0	6.4	5.3	16.2

SD, standard deviation; P25, 25th percentile; P75, 75th percentile; pop, population; Cars, housings without cars; Income, median household income; Work, unemployment rate; Beds, hospital beds.

We found higher accessibility to mobility measurements assessed by walkability, Bike Score and public transportation in Massachusetts is associated with lower COVID-19 rates. The negative associations suggest that higher walkability and accessibility to transportation may be associated with lower risk of COVID-19, or that neighbourhood-built environment inherently contain many social-economic indicators that affect health. In both cases, our findings provide important insights on the communities most at risk for COVID-19 and offer a deeper understanding of the relationship between the built environment and COVID-19 transmissions on a community-level. After the outbreak of COVID-19 pandemic, several research initiatives began to explore the association

Table 2. Characteristics of cities by groups of Walk Score, Transit Score and Bike Score.

Characteristic		Overall pop (no.)	Pop density (persons/mile^2)	Hispanic pop (%)	Black pop (%)	Cars (%)	Income (USD)	Work (%)	Beds/ 1000	Pop >65 (%)
Total (n=72)	Mean	57687.1	4396.6	13.3	5.9	11.7	86084.7	4.7	3.4	16.3
	SD	81286.7	4176.1	15.0	7.8	7.3	34411.4	1.7	3.3	3.4
	Median	40272.5	2723.1	8.7	3.5	10.3	79074.0	4.4	2.7	16.4
	P25	28164.0	1772.4	4.5	2.1	6.4	60147.0	3.5	0.4	14.2
	P75	58408.5	5312.7	17.0	5.8	16.0	101326.0	5.8	5.9	18.2
Walk Score										
Car-dependent (n=42)	Mean	35441.1	2029.0	9.0	4.4	7.9	91051.5	4.5	3.4	17.7
	SD	12966.6	846.9	8.0	6.7	3.2	36662.2	1.4	3.1	2.8
	Median	30566.0	2037.9	6.7	2.8	7.2	82609.5	4.1	2.7	17.4
	P25	27572.0	1230.5	3.2	1.9	5.4	67862.0	3.5	0.6	15.7
	P75	41885.0	2717.8	9.9	4.5	10.4	100757.0	5.2	5.8	19.6
Somewhat walkable (n=21)	Mean	69591.1	5243.7	16.2	7.5	13.8	78618.4	5.2	4.1	15.3
	SD	44872.7	2171.3	15.2	9.4	5.9	32795.3	2.0	3.7	3.1
	Median	57637.0	4880.0	10.5	5.0	15.4	68808.0	5.1	4.1	15.1
	P25	39814.0	4561.9	4.9	2.9	8.0	56181.0	3.5	0.4	13.6
	P75	94207.0	6822.4	20.8	7.2	18.5	106955.0	6.0	6.6	16.7
Very walkable (n=9)	Mean	133726.0	13468.5	26.9	9.4	24.6	80327.1	4.9	2.3	12.0
	SD	208017.8	3926.4	27.6	7.8	7.6	24873.3	2.0	3.1	2.6
	Median	60984.0	13438.5	12.4	5.6	24.2	71115.0	4.7	0.4	11.2
	P25	46118.0	10762.4	9.2	3.0	19.9	65528.0	3.5	0.0	10.4
	P75	80906.0	16416.8	28.3	16.5	30.2	101103.0	5.2	3.5	12.7
Transit Score										
Missing (n=21)	Mean	30860.5	2127.6	8.6	2.6	7.9	94104.8	4.5	2.9	17.4
	SD	12097.1	1533.3	8.5	1.8	3.6	41038.1	1.7	3.6	3.6
	Median	28696.0	2001.0	5.4	2.3	7.3	80943.0	3.9	0.6	16.8
	P25	20610.0	1230.5	3.0	1.6	4.9	68944.0	3.5	0.0	15.1
	P75	39736.0	2330.9	9.5	3.3	10.7	118721.0	5.0	5.8	20.9
Some transit (n=43)	Mean	54697.7	3904.8	14.3	6.8	11.1	82585.4	4.9	4.0	16.5
	SD	35727.6	2777.4	15.9	9.2	5.8	32723.2	1.7	3.1	3.0
	Median	41606.0	3181.7	8.7	4.1	10.0	74962.0	4.9	3.5	16.7
	P25	28609.0	1779.7	4.3	2.7	6.8	56878.0	3.5	1.1	14.2
	P75	72308.0	4880.0	18.4	6.4	15.7	100757.0	5.9	6.2	18.0
Good transit (n=8)	Mean	144175.3	12995.8	20.5	9.8	24.7	83840.4	4.3	2.0	12.4
	SD	219498.4	4738.2	20.9	6.9	8.0	22360.8	1.3	3.3	2.5
	Median	60082.0	12858.4	11.0	7.4	26.3	83785.0	4.4	0.3	12.1
	P25	55664.5	8691.8	7.7	5.2	18.9	64271.5	3.1	0.0	10.3
	P75	98769.0	17228.8	26.7	13.9	31.2	100241.0	5.2	3.2	14.6
Bike Score										
Somewhat bikeable (n=55)	Mean	44780.0	3315.6	13.4	5.1	9.9	87038.8	4.7	3.3	17.0
	SD	29632.8	2988.5	16.2	8.0	5.8	35875.7	1.6	3.2	3.3
	Median	37220.0	2434.5	7.7	2.9	7.8	80586.0	4.4	2.6	16.9
	P25	27586.0	1612.8	3.3	1.9	5.7	58469.0	3.5	0.4	14.8
	P75	53692.0	3582.4	16.1	5.4	12.1	100757.0	5.7	5.8	19.3
Bikeable (n=13)	Mean	57652.1	5833.5	13.5	8.2	14.0	78618.4	5.2	4.0	14.8
	SD	36280.6	3927.2	11.9	6.5	5.4	31858.7	2.1	3.8	2.6
	Median	45304.0	5184.0	8.7	5.3	11.5	66522.0	4.0	3.7	16.2
	P25	35401.0	2319.1	6.5	3.1	10.5	56905.0	3.6	0.0	12.7
	P75	60984.0	8260.9	17.8	14.9	18.5	101103.0	6.4	6.1	16.6
Very bikeable (n=4)	Mean	235274.3	14589.9	12.1	10.3	29.7	97230.8	4.2	3.7	11.9
	SD	300338.6	4624.1	5.6	8.7	4.5	19330.0	1.7	4.2	2.9
	Median	98769.0	15051.1	11.0	7.8	30.4	100241.0	3.7	2.8	11.3
	P25	70043.0	11178.4	8.2	4.3	26.3	84221.5	3.1	0.3	10.1
	P75	400505.5	18001.5	16.1	16.3	33.2	110240.0	5.3	7.1	13.8

SD, standard deviation; P25, 25th percentile; P75, 75th percentile; pop, population; Cars, housings without cars; Income, median household income; Work, unemployment rate; Beds, hospital beds.

between built environment factors and the spread of COVID-19. Nguyen *et al*. (2020) found that indicators of mixed land use, walkability, and physical disorder were connected to higher COVID-19 cases and indicators of lower urban development were associated with fewer COVID-19 cases. Lee *et al*. (2020) discovered a positive but insignificant association between increasing newly confirmed COVID-19 cases and increasing traffic in Incheon, South Korea. A cross-sectional research study by Emeruwa *et al*. (2020) showed that large household membership and household crowding were associated with COVID-19 transmission among pregnant women. Li *et al*. (2021) found that the density of urban facilities around railway stations, travel time by public transport to activity centres, and the number of flights from Hubei Province were associated with the spread of COVID-19 at its initial stage in China. Kim *et al*. (2021) examined the geographic variation in SES, mobility, and built environmental factors in relation to COVID-19 outcomes and found neighbourhoods with low-density housing were associated with higher COVID-19 case rates.

Walkability, public transit and cycling services are important aspects of the built environment and design of cities and can influence health outcomes. Urbanization is a global trend, with 55% of the global population considered urban dwellers (Ezzati *et al*., 2018). From 2000 to 2010, the proportion of Massachusetts' urban population was steady, only increasing slightly from 91.4% to 92% (Iowa State University, 2021). Empirical evidence shows that urban living brings health benefits to urban residents in high-income as well as low- and middle-income countries, but health inequality within the city is also increasing (Ezzati *et al*., 2018). Walkability, public transit and biking infrastructure can bring health benefits to neighbourhood urban residents and therefore, become influential to health inequality within or among cities.

We hypothesize several mechanisms in which walkability and transportation can potentially influence the transmission of COVID-19. Current evidence indicates that SARS-CoV-2 transmits mainly through airborne droplets (Bourouiba, 2020). Improving neighbourhood walkability may potentially facilitate alternate forms of transportation, like walking and biking, which avoids overcrowding of buses and subways in peak hours

Table 3. Association of Walk Score, Transit Score and Bike Score by tertiles with COVID-19 cases rate in univariate and multivariate models.

Score levels	Model 1 estimate (95% CI)	P-value	Model 2 estimate (95% CI)	P-value	Model 3 estimate (95% CI)	P-value
Every 10 points of Walk Score	255.3 (–247.5, 758)	0.3148	–1462.1 (–2703.9, –220.3)	0.0218	–1089.4 –2240.8, 61.9)	0.0632
Tertile 1 (n=24)	-	-	-	-	-	-
Tertile 2 (n=25)	969 (–1814.8, 3752.9)	0.4897	–594.8 (–3273.7, 2084)	0.6588	–1540.4 (–3529.7, 448.8)	0.1266
Tertile 3 (n=23)	2679.1 (263, 5095.3)	0.0303	1533.9 (–2106, 5173.8)	0.4029	–853 (–3888, 2182)	0.5759
Every 10 points of Transit Score	–394.1 (–1037.6, 249.4)	0.2243	–2133.1 (–3123, –1143.1)	<0.0001	–1915.7 (–3329.4, –502.1)	0.0092
Missing (n=21)	–1051.4 (–4010.4, 1907.7)	0.4808	–322.6 (–3164.8, 2519.5)	0.8213	248.4 (–1870.2, 2367)	0.8153
Group 1 (n=27)	-	-	-	-	-	-
Group 2 (n=24)	885.3 (–1271.2, 3041.7)	0.4156	757.5 (–1878.5, 3393.6)	0.5678	–291.8 (–2441.6, 1858.1)	0.7869
Every 10 points of Bike Score	–643.5 (–1227.8, –59.1)	0.0314	–2702.3 (–3349.6, –2055)	<0.0001	–2059.2 (–2882.2, –1236.3)	<0.0001
Tertile 1 (n=26)	-	-	-	-	-	-
Tertile 2 (n=21)	–416.9 (–3261.7, 2427.8)	0.7709	–1065 (–3663.5, 1533.6)	0.4159	–2838.7 (–4720.2, –957.3)	0.0038
Tertile 3 (n=25)	1254.6 (–1111.3, 3620.4)	0.2938	–596.7 (–3719.5, 2526.2)	0.7039	–2912.6 (–5238.6, –586.7)	0.015

Model 1 was the univariate model. Model 2 was adjusted for log-transformed population density, percentage of population over 65, and tertiles of race variables in the table. Model 3 was additionally adjusted for percentage of households without cars, unemployment rate, hospital beds per 1000, and tertiles of income variables in the table. All models were population weighted.

Table 4. Association of Walk Score, Transit Score and Bike Score by groups with COVID-19 cases rate in univariate and multivariate models.

Score levels	Model 1 estimate (95% CI)	P-value	Model 2 estimate (95% CI)	P-value	Model 3 estimate (95% CI)	P-value
Every 10 points of Walk Score	255.3 (–247.5, 758)	0.3148	–1462.1 (–2703.9, –220.3)	0.0218	–1089.4 (–2240.8, 61.9)	0.0632
Car-dependent (n=42)	-	-	-	-	-	-
Somewhat walkable (n=21)	2307 (91.2, 4522.7)	0.0415	–970.4 (–3881.2, 1940.3)	0.5077	–2613.9 (–5163.9, –63.9)	0.0447
Very walkable (n=9)	1087.1 (–1245.4, 3419.6)	0.3557	–5576.3 (–10790.1, –362.5)	0.0365	–3712.7 (–8675.6, 1250.3)	0.1397
Every 10 points of Transit Score	–394.1 (–1037.6, 249.4)	0.2243	–2133.1 (–3123, –1143.1)	<0.0001	–1915.7 (–3329.4, –502.1)	0.0092
Missing (n=21)	–2149.8 (–4829.9, 530.3)	0.1141	235 (–2251.1, 2721.1)	0.8508	366.5 (–1712.9, 2446)	0.7255
Some transit (n=43)	-	-	-	-	-	-
Good transit (n=8)	–1600.3 (–3771.8, 571.3)	0.1461	–5281.2 (–7910.5, –2652)	0.0002	–787.1 (–3874.5, 2300.3)	0.6118
Every 10 points of Bike Score	–643.5 (–1227.8, –59.1)	0.0314	–2702.3 (–3349.6, –2055)	<0.0001	–2059.2 (–2882.2, –1236.3)	<0.0001
Somewhat bikeable (n=55)	-	-	-	-	-	-
Bikeable (n=13)	97.5 (–2402.5, 2597.5)	0.9382	–1373 (–3159.3, 413.3)	0.1295	–2045.1 (–3694.2, –395.9)	0.016
Very bikeable (n=4)	–2442.9 (–4739.5, –146.3)	0.0374	–7818.8 (–10048.2, –5589.4)	<0.0001	–9774 (–14348.2, –5199.8)	<0.0001

Model 1 was the univariate model. Model 2 was adjusted for log-transformed population density, percentage of population over 65 and tertiles of race variables in the table. Model 3 was additionally adjusted for percentage of households without cars, unemployment rate, hospital beds per 1000 and tertiles of income variables in the table. All models were population weighted.

(Delgado-Ron, 2020). Parks, a component of the Walk Score, also enable outdoor exercise with adequate social distance and can function as a safety valve when communities are otherwise engaged in non-pharmacologic interventions and social distancing measures for COVID-19. Ultimately, Walk Score, Transit Score and Bike Score indicate differential access to modes of mobility, allowing people to flexibly decide their routes to amenities and of commuting. This relationship with commuting bears further research, given the known relationship with occupational exposure of essential health workers to COVID-19 as well as other risk groups disproportionately impacted by COVID-19 such as racial minorities. Understanding the complex relationship of how the structure of the urban environment may constrain commuting patterns for essential workers during COVID-19 would offer potential insights on future pandemic preparedness and response.

Walk Score, Transit Score, and Bike Score are useful and valid indicators for urban walkability, public transit and biking services. Duncan *et al*. (2011) evaluated the validation of Walk Score for estimating neighbourhood walkability and confirmed it as a reliable measure, particularly for the vicinity of around a 1600-meter buffer spatial range. Carr *et al*. (2011) also found significant correlations between Walk Score and access to walkable amenities within a 1-mile buffer. However, a systematic review by Hall and Ram (2018) assessed the validity of Walk Score used as an adjustment variable. Duncan *et al*. (2013) confirmed the validity of Transit Score for the significant correlations between Transit Score and GIS measures of neighbourhood transit availability, while Winters *et al*. (2016) explored the association between Bike Score and cycling behaviour in 24 US and Canadian cities and found significant relationships at the city and census tract level.

Our study adds additional evidence to the current research of COVID-19 in Massachusetts. A cross-sectional study of 351 Massachusetts towns or cities examined the community-level racial and ethnic characteristics and their impact on COVID-19 rates, which found significant associations between race distribution and COVID-19 rates (Figueroa *et al*., 2020). This association was further demonstrated by the high seroprevalence of anti-SARS-CoV-2 antibodies in Chelsea, Massachusetts with high population density and a large Hispanic population (Naranbhai *et al*., 2020). Our findings of a strong relationship between neighbourhood income with COVID-19 cases is consistent with the broader literature on COVID, which has shown an association of higher poverty, more crowded households, more ethnic minorities and higher racialized economic segregation with COVID-19 (Chen *et al*., 2020). Emerging data suggests that workers that are considered essential, or those whose occupations require their physical presences are more likely to be ethnic minorities, immigrants, or in blue-collar professions (Figueroa *et al*., 2020). These populations experience disproportionately higher risk in contacting SARS-CoV-2 (Naranbhai *et al*., 2020). If demographic characteristics and occupational type with higher risk were associated with less walkable residential locations then there is potential for an effect confounding factors; however, in our analysis, we saw that ethnic minorities (Hispanic and Black populations) tended to live in places with higher walkability and transportation, so this effect is in the opposite direction of our finding. A research article by Kim *et al*. (2021) is also consistent with our findings.

Our results identify the built environment as an additional layer of social determinants of health that adds context to the current literature the vulnerability to COVID-19 based on race or income. Communicable disease overwhelmingly affects those with fewer means to prevent exposure. People with lower social-economic resources may be at a higher proportion of occupations that need physical presence and cannot work from home. A study found that a 10% increase in the Black population was associated with a 312.3 per 100,000 increase in COVID-19 cases, and the same percentage point increase in the Latino population was associated with an increase of 258.2 COVID-19 cases per 100,000 (Figueroa *et al*., 2020). People of foreign origin and larger household sizes were also associated with higher COVID-19 rates (Figueroa *et al*., 2020); likely because the lack of space to socially distance or essential employment duties at work. In our study, we analysed SES and racial factors and found that people with lower income and of ethnic minorities tend to live in places that are more urban, hence with higher walkability (Tables S3-S5 in Appendix). The same group of the population had higher rates of COVID-19. Thus, the direction of potential confounding is likely to be towards null in our analysis.

Our study has several strengths. First, this is the first study to employ a novel exposure metric in examining the association between walkability and COVID-19 rates as Walk Score contains updated measurements of walkability. Second, our findings have important and timely public health implications for the current policy discourse. For example, do closure of parks and other facilities truly protect the public from COVID-19, or could it inadvertently cause people to congregate in other enclosed spaces. Third, we had a wide range of covariates to adjust for, ranging from SES variables and availability of hospital resources. However, also limitations apply. Primarily, this is an ecological and cross-sectional study, and our findings do not imply causality. Walk Score, Transit Score, Bike Score and other city-level variables were collected before the outbreak of COVID-19 and may not reflect more recent changes resulting from the COVID-19 pandemic. Second, we did not have household addresses of COVID-19 cases through our public access data sources. Therefore, we could not analyse the association at a more granular level. Further analysis on hospitalization and vaccine uptake is needed. Third, the Walk Score website only provided the city-level Walk Score, Transit Score and Bike Score ratings for the 72 most populated cities in Massachusetts. When calculating the city-level Walk Score, Transit Score and Bike Score, biases may be introduced because of Modifiable Areal Unit Problem (MAUP). The city-level Walk Score may not be relevant for individuals living in a wide range of environments within a city. As these scores are proprietary algorithms, we relied on the accuracy of the publicly available versions of these scores. Fourth, cities or towns with populations fewer than 10,000 did not have a Walk Score and were not included in our analysis. Lastly, there may be statistical collinearities and interdependences between variables based on this commercially available data source, which may have more intricate relationship with disease co-morbidities that we did not explore fully.

Conclusions

Although our findings reveal important public health implications for current policies, we need further research on neighbourhood-level metrics to elucidate the pathways of transmission to better understand the role of the built environment in the COVID-19 pandemic. The findings presented here suggest that the communities in which we live may have a profound consequence on our health based on commercially available walkability and transportation indices. We would appreciate more research using individual-level data to further investigate the complex association between built environment and COVID-19 pandemic. For ecological studies, data with smaller geographic units and larger sample sizes can be utilized to reveal geographic variations of the association using weighted geographical regressions methods. Studies with other walkability indicators are also needed.

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