Built and Social Environment Impact on Covid-19 Transmission

MING HU
University of Maryland

Keywords: COVID-19, built environment, social environment, D.C.

The goal of this research was to investigate the multifaceted interrelationships between the built and social environments and the impact of this relationship on population-level health in the context of the novel coronavirus disease 2019 (COVID-19). More specific, this study assessed the relationship between several social determinants of health, including housing quality, living condition, travel pattern, race/ethnicity, household income, and COVID-19 outcomes in Washington, D.C (DC). Using built environment and social environment data extracted from DC energy benchmarking database and the American Community Survey database, more than 130,000 housing units were analyzed against COVID-19 case counts, death counts, mortality rate, age adjusted incidence rate and fatality rate data for DC wards. The results demonstrated that housing quality, living condition, race and occupation were strongly correlated with COVID death count.

INTRODUCTION

Substantial scientific evidence gained in the past decade has shown that various aspects of the built environment can have profound and directly measurable effects on both physical and mental health outcomes at the population level.[1] These effects have been particularly impactful to the already existing burdens of illness experienced among low-income populations and communities of color. [1-3] However, there are two primary gaps. First, clearly demonstrating the connection between built environment and health disparities has proven to be challenging to the scientific community due to a variety reasons, such as a need for detailed and quality neighborhood data as well as location-based built environment data. Traditional studies have often lumped many important components of the built environment into a blanket socioeconomic status variable. But this approach makes it nearly impossible to tease out discrete housing and community characteristics related to certain diseases [[1]]. Second, in the past couple decades, the focus on the association between the built environment and public health has been mainly focused on chronic disease rather than infectious disease .[4] Specifically, in many countries around the world the devastating ascent of childhood and adult obesity rates in addition to obesity related chronic diseases has gleaned the attention of active living researchers.[5] [6] As such, built environment factors related to physical activity, including sidewalks. [7 8], bike paths,[9] greenspace[10, 11], and recreation facilities [12], have been studied extensively. Limited studies have focused on built environment factors linked to indoor air quality and subsequently infections disease, such as the physical and structural condition of buildings and homes [13].

The novel coronavirus disease 2019 (COVID-19), caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), was detected in December 2019. Following the original site of detection, Wuhan, China, infections spread across China and other countries around the world. In January 2020, COVID-19 was first confirmed in the United States when a man was diagnosed after returning to Washington State from travel in Wuhan, China. When there were over 125,000 cases and 4500 deaths worldwide, the World Health Organization classified the COVID-19 outbreak a pandemic in March 2020.[14]. As of August 1, 2020, there were over four and half million confirmed cases and 154,333 deaths in the United States.[15]. Since the beginning of the pandemic, there has been a surge of research focused on the impact of built environment factors, such indoor air quality and building design, in the transmission of infectious disease environmentally mediated pathways. [16-18] Most studies have focused on the strategies for reopening office buildings [19-20] and schools.[21] However, there has been limited research on residential housing. [22] In the foreseeable future, the majority of people will continue to work from home either entirely or partially Therefore, it is essential to understand the influence of housing quality on public health in the context of COVID-19 in order to provide knowledge and insights to policy makers and other stakeholders. To this extend, this study addresses such gap by examining the association of built environment and social-economic factors with COVID-19 incidence, mortality and fatality rates.

1.0 INFLUENCING FACTORS

1.1 BUILT ENVIRONMENT FACTORS

Poor housing and building quality has been found to be associated with mold, moisture, and dust mites, which can trigger a variety of health issues including asthma and other respiratory conditions [8]. Studies have shown that negative aspects of poor housing and built environment conditions can magnify health disparities and exacerbate already distressing conditions [1]. Housing quality, a composition of several determining factors, has been defined as "the physical condition of a person's home as

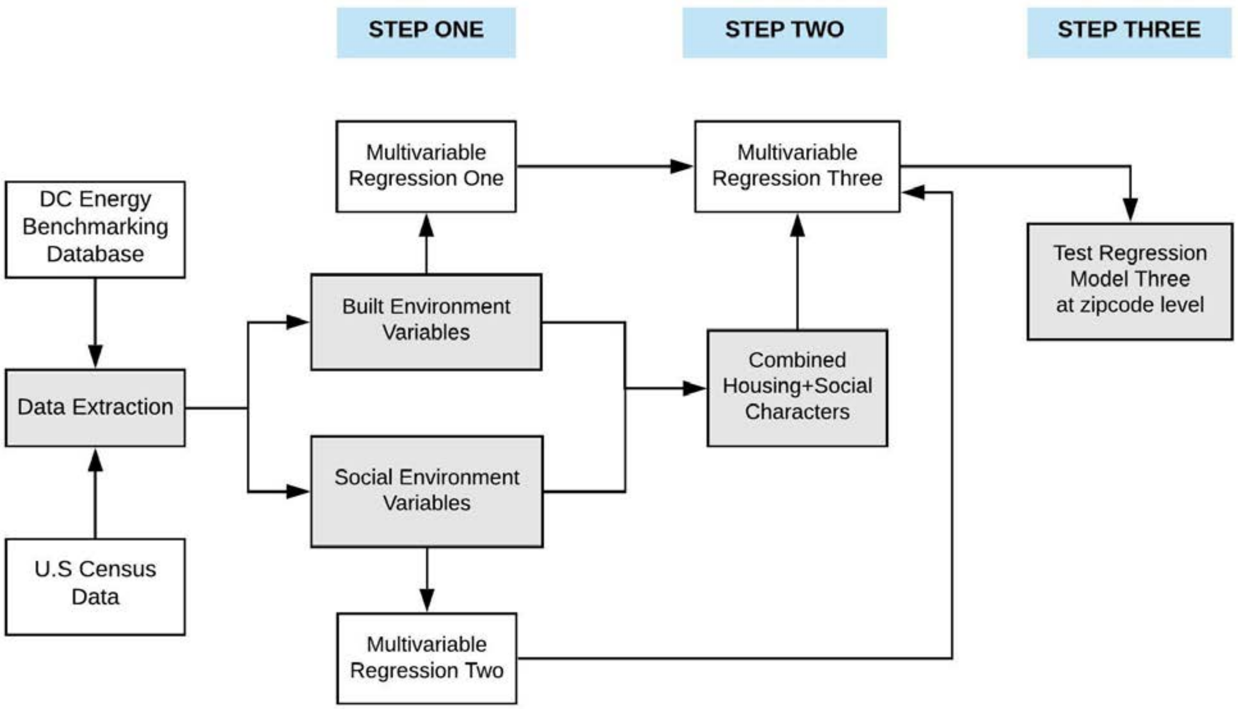


Figure 1. Research Methodology

well as the quality of the social and physical environment in which the home is located" [ ]. In this study, seven factors used to index built environment and housing quality and impact have been identified: (1) housing age (HA); (2) housing size (HS); (3) housing energy efficiency (HEE); (4) crowding ratio (CR); (5) greenspace ratio (GSR); (6) DC student who lives and attends school in the same wards ratio (STR); and (7) commute time to work (CT).

HEE, HA and HS together was used as a proxy measure of housing physical condition. The United States did not employ a national model building energy code until 1994 [ ]. Therefore, without energy retrofit older houses are generally less energy efficient. As such, this research assumed that older buildings with good energy performance underwent renovation, and maintenance/operation has been kept up to date. And those factors together are standard indicators for the condition of housing units. CR and GSR together was used as a proxy measure of residents' living condition. CR is different from urban density. Urban density, which maintains attributes of behavior and flow, describes the dimensions of relationships between attributes of urban substance. Specifically, it is a measurement of the number of houses per acre or the number of people per acre and provides insight on how close the buildings or houses are located to one another [ ]. Crowding measures how many households have more occupants than rooms. Previous study have shown that urban density positively relates to the number of current COVID-19 cases, but the effect is relatively small [ ]. Compared to urban density, household crowding is a strong predicator of the COVID-19 risk. There has been consistent analysis demonstrating the correlation between crowding and COVID-19 cases in New York City [ ], Chicago [ ] and other major metropolitan areas. GSR was used as a proxy for measuring access to greenspace. Generally speaking greenspace access has a positive impact on physical and mental health [ ]. And, the racial disparity in access to greenspace has well documented. There are spatial and social disparities in tree canopy coverage[1], park quality[2, 3], and even how greenspace is distributed[4]. During the COVID-19 social distancing mandates, there were numerous reports of inequities related to the availability of safe parks in cities across the country [5-7]. STR and CT measured the adjacency between housing to school and work, together they measured the residents' travel pattern.

1.2 SOCIAL ENVIRONMENT FACTORS

In this study, data from the American Community Survey (ACS) database, which has four subject areas: social, economic, housing and demographic, were used. Eight social-economic variables were identified at ward level: (1) Black American ratio (BAR); (2) median age (MA); (3) age>65 ratio (A65), (4) median household income (HI); (5) poverty rate (PR); (6) family to non-family household ratio (FNR); (7) foreign born ratio (FBR); (8) essential to non-essential worker ratio (ENR) (Table 2). BAR, which is defined as the ratio of Black or African Americans to White Americans, MA and A65 together represented the vulnerable population ratio by ward; this category was defined as demographic status. HI, PR were used to present economic status. FNR and FBR together represented household composition category. The ENR defined the occupation category. The ACS provides the count of the number of workers over age 16 within a given ward, as well as the count employed in each of 5 discrete categories; management, business, science and arts occupations; service occupations; sales and office occupations; natural resources, construction and maintenance occupations; and production, transportation and material moving occupations. Based on the DC government definition of "Essential" and "Non-Essential" workers during the period of the COVID-19 shutdown, the service, natural resources, and production/transportation categories of occupation were considered to be "Essential". The remaining categories of management and sales were considered "Non-Essential" occupation categories. The ENR is the sum of the population in the "Essential" categories in a given ward was divided by the sum of the "Non-Essential" workers in the given ward to get a proportion of Essential to Non-Essential workers.

2.0 METHOD AND DATA COLLECTION

As illustrated in Figure 1, the research methodology of this study was composed of three steps. For each step, separate multivariable regression models were created, in order to determine the association between built and social environment variables with COVID-19 outcomes. In step one, the built environment (housing) variables were grouped into three categories assuming their interrelated nature: Housing Quality (HA, HS, HEE), Living Condition (CR, GSR), and Travel Pattern (CT, STR). These built environment variables were then regressed on current COVID-19 outcomes. The same method was used to examine current COVID-19 outcomes in relation to the social environment characteristics of DC residences. The most influential built environment and social environment variables were identified at wards level from the regression models. Then, in the second step, the most influential predicators from each domains were combined to create a multivariable regression model. In the last step, the combined model was tested at neighborhood level for this robustness. In addition, based on the combined regression model, a geographic heat map was generated to project the potential cases at zipcode level, in order to identify the hot spots at the neighborhood level, and make suggestion on allocating more sources to those potential hot spots

2.1 DATA ACQUISITION

Housing character data were downloaded from DC Energy Benchmark database. In 2008, DC passed the Clean and Affordable Energy Act (CAEA), which requires that all buildings with a gross floor area of 50,000 ft2 (4,645 m2) or greater to report their actual building energy and water use annually. The benchmarking is done according to the ENERGY STAR Portfolio Manager® by the U.S. Environmental Protection Agency. It was developed to provide a method for comparing the energy consumption of a building with that of similar activities, adjusting for size, climate, and operational characters. This method makes it possible to determine each buildings' age, size, location, and current physical condition (use EUI as indicator). Since 2012, the DC has released energy benchmarking data for more than a thousand buildings under the benchmarking law. It includes multifamily residences, offices, education buildings, mixed-use buildings, hospitals, libraries, hotels, K-12 schools, among others. For this study, the dataset from 2019 (based on 2018 operations), which has the highest data reporting compliance (1,343 buildings) was used. Among all buildings included in the 2019 report, buildings that were exempt from 2019's disclosure, those that currently have data under review, and those with no report received were excluded, which resulted in 1,333 buildings. Of those buildings, there were multifamily housing (672), total 116,732,026ft2. The average unit size in DC is around 844 ft2, so all together around 138,298 units are reported in 2019 DC Energy Benchmark database. The released data includes both descriptive and energy use information; appendix table A1 lists the specific information released for each building [9]. Meanwhile, the U.S. Census Bureau's 2010-2014 ACS, reports approximately 357,815 housing units including single unit housing for DC. The single-unit to multi-units housing ratio is around 0.606. Hence, the multi-unit s(multifamily) housing in DC is around 140,979 units. As such, it can be concluded that the multifamily housing units data extracted from the energy benchmarking database represents the normal distribution (>98%) of the overall multifamily housing units in DC. Social demographic data were extracted from the ACS database to calculate age, race, occupation, household composition, commute, and crowding ratio at the ward level. For detailed explanation, refer to appendix. Finally, the COVID-19 outcome data was extracted from the DC government coronavirus online dashboard, which published daily statistics. The data include total COVID-19 case counts, age adjusted incidence rates and death counts by ward, race, sex, and age. Using these data, COVID-19 mortality and fatality rates by ward were calculated. This study used data from August 02,2020 . (Figure 2).

2.2 STATISTIC ANALYSIS

As mentioned previously, a three-step analysis was used (Figure 3). First, separate multi-variable regression models were created for built environment factors and social environment factors. After determining the influential predictors (significant variables), multicollinearity test were conducted to determine the dependence of those variables. Variables that were highly dependent on other variables (VIF >10 is used as cut score) were ruled out. Then the fitness of the built environment model and social environment model were compared within the dataset using the likelihood ratio test (LRT) to determine the power of the models. Lastly, the most influential built environment predictors and social economic predictors were combined into a final multi-variable regression model to study the dynamics of those predicators to relation of COVID-19 outcomes. In order to determine if different categorical built environmental variables could explain the relationship between built environment conditions and current COVID-19 development, three multi-variable regression models were created and adjusted for demographics (Eq. 1-3). COVID-19 outcomes of case count, death count, mortality rate and fatality rate, and the age adjusted incidence rates were the dependent variables.

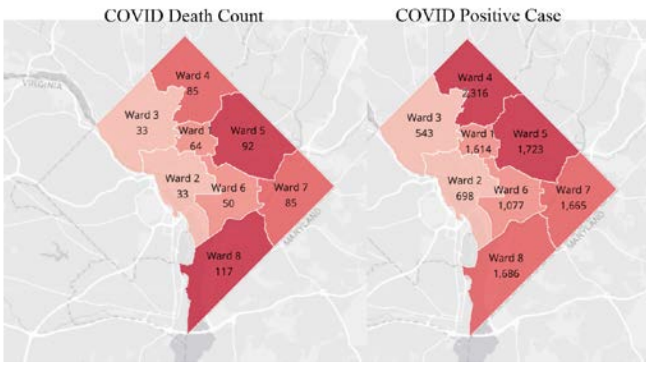


Figure 2.

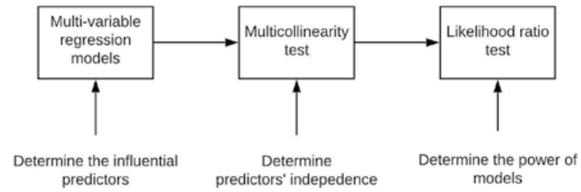
Following the same procedure used for built environment variables, four multi-variable regression models were created and adjusted for demographics (Eq.4-7) to determine the relation between social environment factors and COVID-19 outcomes.

3.0 FINDINGS AND RESULTS

3.1 BUILT ENVIRONMENTAL VARIABLES

DC housing unit types included 1-unit, detached (detached single-family house), 1-unit, attached (attached detached single-family house), and 2 units, 3 or 4 units, 5 to 9 units (low-rise multistory, multi-family housing), 10-19 units, 20 or more units (high-rise multistory, multi-family housing) (Figure 4). Ward 2 provided the most units, followed by Ward 6, Ward 3 and Ward 1, respectively. The most common housing types in Wards 1, 2, 3 and 6 were "10-19 units" and "20 or more units" high-rise multistory, multi-family housing, which were accompanied with a relatively low crowding ratio. On the contrary, Wards 4, 5, 7, 8 had predominately a single-family housing type, but with higher crowding ratio. Specifically, in Ward 4, there were the fewest amount of housing units, but with the second highest crowding ratio in DC. The crowding ratio was calculated based on aggregated data extracted from United States Census Bureau.

For median housing age, Ward 6 had the newest and largest building stock. Ward 1 had the oldest housing stock and highest energy efficiency. With the lowest source EUI, this was an indication that these older Ward 1 buildings underwent some building system renovations or upgrades, hence it was possible that these housing units had a better physical quality than some of the newer buildings in other wards. In terms of crowding, the homes with more than 1.5 persons per range were counted as severely crowded and the homes with 1.01-1.5 persons were considered moderately crowded [ ]. Ward 1 had the highest crowding ratio (6.1%), followed by Ward 4 (4.3%) and Ward 8 (4.5%). Overall, the crowding ratio was aligned with housing types, and the townhouses (1-unit, attached) contributed to the most to crowding ratio (Figure 4). The availability of greenspace followed a similar trend as CR, except for Wards 3 and 4 having a GSR of 5.8 and 4.0, respectively. Ward 8 had the longest commute to work time (36.5



For Demographic Status (BAR, MA, A65)

$$Y_i = \beta_0 + \beta_1(BAR) + \beta_2(MA) + \beta_3(A65) + \mu_i \qquad \text{Eq.4}$$

For Economic Status (HI, PR)

$$Y_i = \beta_0 + \beta_1(HI) + \beta_2(PR) + \mu_i \qquad \text{Eq.5}$$

For Household Composition (FNR, FBR)

$$Y_i = \beta_0 + \beta_1(FNR) + \beta_2(FBR) + \beta_2(ENR) + \mu_i \qquad \text{Eq.6}$$

For Occupation (ENR)

For Demographic Status (BAR, MA, A65)

$$Y_i = \beta_0 + \beta_1(BAR) + \beta_2(MA) + \beta_3(A65) + \mu_i \qquad \text{Eq.4}$$

For Economic Status (HI, PR)

$$Y_i = \beta_0 + \beta_1(HI) + \beta_2(PR) + \mu_i \qquad \text{Eq.5}$$

For Household Composition (FNR, FBR)

$$Y_i = \beta_0 + \beta_1(FNR) + \beta_2(FBR) + \beta_2(ENR) + \mu_i \qquad \text{Eq.6}$$

For Occupation (ENR)

$$Y_i = \beta_0 + \beta_1(ENR) + \mu_i \qquad \text{Eq.7}$$

Figure 3.

mins) followed by Ward 4 (32.9 mins) and 5 (30.9 mins). Ward 8 also had the highest rate of students attending the school in the same ward (79%), followed by Ward 7 (68%) and 3 (57%).

3.2 SOCIAL ENVIRONMENTAL VARIABLES

Approximately 13.5% of all DC families live below the poverty line, yet Ward 7 (27.7%) and 8 (36.8%) had poverty rates more than double the average DC rate. [25] As such Wards 7 and 8 also have the most homogeneous populations with nearly all African American residents as indicated by BAR values of 0.95 and 0.94, respectively. Interestingly Ward 8 had the lowest median age (28.9 years) as well as the highest family to non-family ratio (1.45). This may indicate several households with boarders or renters mixed in with families. Ward 4 had the highest FBR with 0.22 while Ward 8 had the lowest with 0.03. Finally, the highest proportions of essential workers were residents of Wards 7 (0.64) and 8 (0.76). Wards 7 and 8 had the highest percentage of workers in retail, healthcare and food services, industries that were determined to be essential. [39]

3.3 REGRESSION ANALYSIS—COMBINED BUILT AND SOCIAL ENVIRONMENTS

Based on results from the previous regressions, built and social environment variables were included into the final combined regression. Results revealed that the overall regression model for

PAPER

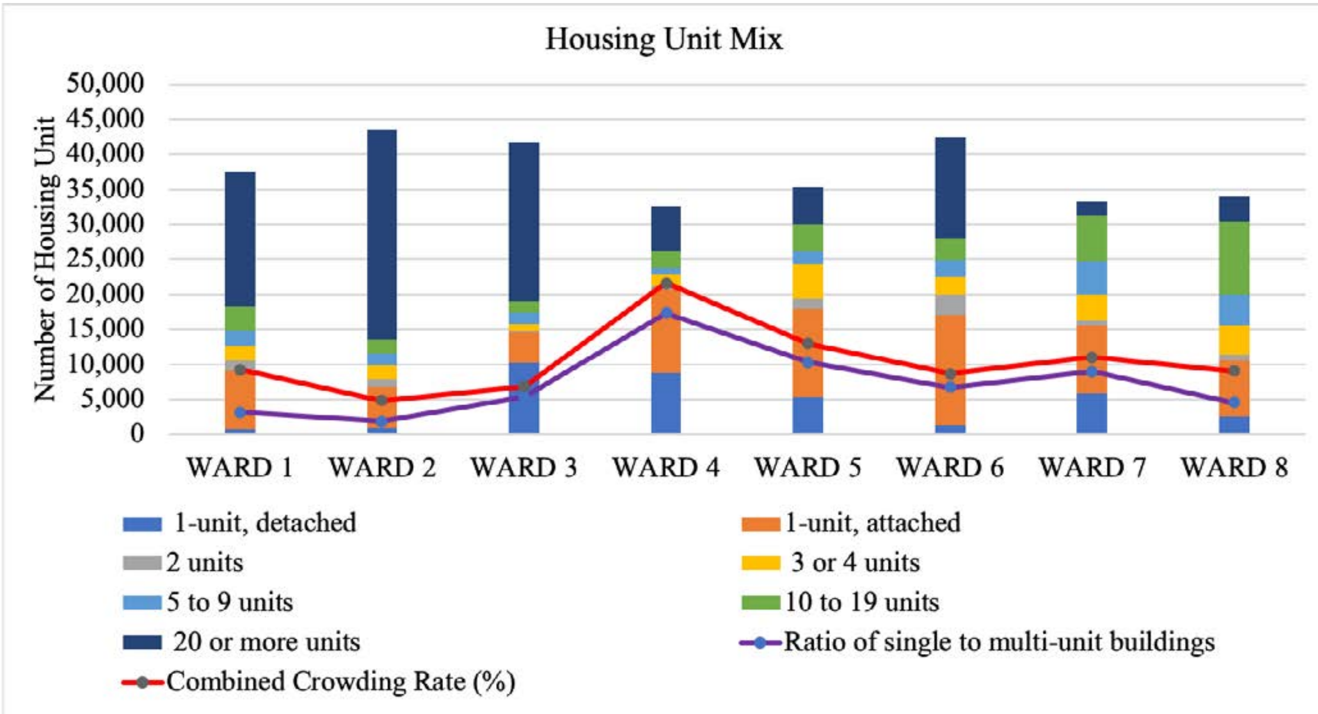


Figure 4. Washington DC Housing Unit Mix.

death count was statistically significant (F=76.50; p=0.0129). High percentage (99.9%) death case was explained by the combination of built and social environment (HA, HS, HEE, CR, CT, BAR, HI, ENR) predicators. However, among the individual variables , only CR showed statistical significance (p<0.05). It can concluded that based on the current available COVID-19 information, the identified combined built and social environment variables are the strongest and most significant predicators of COVID-19 death counts.

4.0 DISCUSSION AND CONCLUSION

This study identified a strong association of built and social environment variables, including housing age, housing size, housing energy efficiency, crowding ratio, work commute, Black American ratio, and essential worker ratio, with the COVID-19 death count in Washington, DC. From the built environment quality perspectives, our findings aligned with other research examining the impact of housing on public health, such as children's asthma prevalence, adult's respiratory issues, health status among residents of color, and youth mental health. This research added new knowledge on the role of built and social environments in the current COVID-19 pandemic by systemically comparing COVID-19 outcomes across a range of housing and living conditions in DC, one of the regions in United States with the highest COVID-19 cases and deaths per population since the onset of the pandemic. DC wards with poorer built environments, specifically housing quality, were found to be associated with a higher COVID-19 death count, even after adjusting for individual risk factors, such as race and household income. For example, Ward 4, which had the lowest supply of housing units (9.13%) and the third highest crowding ratio (3.0%), maintained the highest the COVID-19 positive case count as of August 2, 2020. Yet, the highest death count was found in Ward 8, which had the second highest crowding ratio (3.4%). This finding corresponds with previous crowding research showing an association between crowding and the transmission of respiratory infections. Overcrowded housing conditions in an urban area like Ward 8, presented a consummate opportunity for increased COVID-19 health risk. Ward 7 had the second highest death count and second lowest supply of housing units (9.29%) [51]. Therefore, those two wards (7 an 8), especially zip code 20020 should be given more attention, provided more testing facilities and health care service in order to prevent the future potential outbreak. From the social environment perspective, this research also aligns with other recent studies. It was determined that BAR was a significant predictor of COVID-19 death count in the uncombined model. This finding was not unexpected considering that Wards 7 and 8 have the highest percentage of African American residents, thus the highest BAR values. As of August 17, 2020, African American residents held the highest percentage (74%) of COVID-19 deaths throughout all of DC. Similarly, the U.S. has experienced a race based disparity of COVID-19 mortality whereby, the COVID-19 death rates for the African American population in some areas was double or more the actual African American population (e.g., 70% vs. 32% - Louisiana; 41% vs. 14% - Michigan). Although some of these COVID-19 death rates for the African Americans have decreased the disparity still persist in many areas throughout the U.S. including the nation's capital.

ENDNOTES

1. Hood, E. (2005). Dwelling disparities: how poor housing leads to poor health.
2. The DRA Project (Accelerating Disparity Reducing Advances). Using Healthy Eating and Active Living Initiatives to Reduce Health Disparities. Bethesda, MD: Institute for Alternative Futures; 2007. Accessed August 3, 2020. https://cdn.ymaws.com/chronicdisease.site-ym.com/resource/resmgr/healthequity/he_dra_report_08_01_using_he.pdf
3. Saarloos, D., Kim, J. E., & Timmermans, H. (2009). The built environment and health: Introducing individual space-time behavior. International Journal of Environmental Research and Public Health, 6(6), 1724-1743.
4. Perdue, W. C., Stone, L. A., & Gostin, L. O. (2003). The built environment and its relationship to the public's health: the legal framework. American journal of public health, 93(9), 1390-1394.
5. Bhurosy, T., & Jeewon, R. (2014). Overweight and obesity epidemic in developing countries: a problem with diet, physical activity, or socioeconomic status?. The Scientific World Journal, 2014.
6. Sallis, J. F., Cutter, C. L., Lou, D., Spoon, C., Wilson, A. L., Ding, D., ... & Mignano, A. (2014). Active living research: creating and using evidence to support childhood obesity prevention. American journal of preventive medicine, 46(2), 195-207.
7. Knuiman, M. W., Christian, H. E., Divitini, M. L., Foster, S. A., Bull, F. C., Badland, H. M., & Giles-Corti, B. (2014). A longitudinal analysis of the influence of the neighborhood built environment on walking for transportation: the RESIDE study. American journal of epidemiology, 180(5), 453-461.
8. Kelly, C. M., Schootman, M., Baker, E. A., Barnidge, E. K., & Lemes, A. (2007). The association of sidewalk walkability and physical disorder with area-level race and poverty. Journal of Epidemiology & Community Health, 61(11), 978-983.
9. Karnik, S., & Kanekar, A. (2012). Childhood obesity: a global public health crisis. International journal of preventive medicine, 3(1), 1.
10. Wolch, J. R., Byrne, J., & Newell, J. P. (2014). Urban greenspace, public health, and environmental justice: The challenge of making cities 'just green enough'. Landscape and urban planning, 125, 234-244.
11. Kessel, A., Green, J., Pinder, R., Wilkinson, P., Grundy, C., & Lachowycz, K. (2009). Multidisciplinary research in public health: A case study of research on access to greenspace. Public health, 123(1), 32-38.
12. Taylor, W. C., Floyd, M. F., Whitt-Glover, M. C., & Brooks, J. (2007). Environmental justice: a framework for collaboration between the public health and parks and recreation fields to study disparities in physical activity. Journal of Physical Activity and Health, 4(s1), S50-S63.
13. Spengler, J. D., & Sexton, K. (1983). Indoor air pollution: a public health perspective. Science, 221(4605), 9-17.
14. Roberts, J. D., & Tehrani, S. O. (2020). Environments, Behaviors, and Inequalities: Reflecting on the Impacts of the Influenza and Coronavirus Pandemics in the United States. International Journal of Environmental Research and Public Health, 17(12), 4484
15. Smith, M., Yourish, K., Almukhtar, S., Collins, K., Ivory, D., & McCann, A. (2020). Coronavirus in the US: Latest map and case count. The New York Times. Accessed August 3, 2020. https://www.nytimes.com/interactive/2020/us/coronavirus-us-cases.html
16. Dietz, L., Horve, P. F., Coil, D. A., Fretz, M., Eisen, J. A., & Van Den Wymelenberg, K. (2020). 2019 novel coronavirus (COVID-19) pandemic: Built environment considerations to reduce transmission. Msystems, 5(2)
17. Bolashikov, Z. D., & Melikov, A. K. (2009). Methods for air cleaning and protection of building occupants from airborne pathogens. Building and Environment, 44(7), 1378-1385.
18. Neal T. COVID-19 and the Built Environment. Colin, Biggers and Paisley Lawyers. [(accessed on 30 April 2020)]; Available online: https://www.cbp.com.au/insights/insights/2020/march/covid-19-and-the-built-environment.
19. The Harvard Gazette. " A five-layered defense for workplace reopening.". accessed July 20, 2020. https://news.harvard.edu/gazette/story/2020/04/looking-at-covid-19-through-healthy-building-eyes/
20. Forbes. "Why COVID-19 raises the stakes for healthy buildings." Accessed July 20, 2020. https://www.forbes.com/sites/hbsworkingknowledge/2020/06/08/why-covid-19-raises-the-stakes-for-healthy-buildings/#1babce5324cd
21. The Harvard Gazette. "Healthy buildings expert outlines recommendations for school reopening." Accessed July 20, 2020. https://news.harvard.edu/gazette/story/2020/06/harvard-expert-outlines-recommendations-for-school-reopenings/
22. Guyot, K., & Sawhill, I. V. (2020). Telecommuting will likely continue long after the pandemic.