Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
Associations between body mass index, physical activity and the built environment in disadvantaged, minority neighborhoods: Predictive validity of GigaPan® imagery

Cathy Antonakos a, Ross Baiers a, Tamara Dubowitz b, Philippa Clarke c, d, Natalie Colabianchi a, d, *

a Environment and Policy Lab, School of Kinesiology, University of Michigan, Ann Arbor, MI, USA
b RAND Corporation, Pittsburgh, PA, USA
c Department of Epidemiology, School of Public Health, University of Michigan, Ann Arbor, MI, USA
d Institute for Social Research, University of Michigan, Ann Arbor, MI, USA

A B S T R A C T

Background: The built environment has been shown to influence health in studies of disadvantaged populations using different measurement methods. This study determined whether environmental exposures derived from GigaPan® images could serve as valid predictors of body mass index (BMI), walking and moderate to vigorous physical activity (MVPA) in a longitudinal study of low-income adults living in two primarily African American neighborhoods in Pittsburgh, Pennsylvania, USA. GigaPan® is a robotic system used to obtain high-resolution, panoramic images of environments.

Methods: Microscale environmental features along 481 streets were audited in 2015–2016 using an audit form. Environmental exposures were estimated for 731 adult participants, using a sample of street segments within a 0.4 km (0.25 mile) network distance from each participant’s residential address. Summary environmental exposures were constructed using factor analysis. We tested associations between participant-level environmental exposures and objectively measured BMI, self-reported walking and objectively measured MVPA in regression models controlling for baseline health and demographic variables.

Results: Three factors representing participants’ environmental exposures were constructed: pedestrian bicycle-amenities; hilly-vacant-boarded; physical activity-recreation/low housing density. Environments with infrastructure and amenities supportive of walking and bicycling were associated with lower BMI (Coef. = -0.47, p = 0.02). Frequent walking was less likely in environments with more physical activity and recreation venues/low housing density (OR = 0.81, 95% CI [0.67, 0.96]). MVPA was not associated with any of the environmental measures and the hilly-vacant-boarded factor was not associated with any of the outcomes.

Conclusions: Predictive validity was demonstrated for an environmental exposure factor that captured features supportive of walking and cycling in a model predicting BMI, using built environment audit data from GigaPan® imagery. A complementary analysis found lower odds of frequent walking in the neighborhood among participants with exposure to more physical activity and recreational features, but fewer types and lower density of housing.

1. Introduction

Physical inactivity and obesity are significant health issues in the USA, and across much of the world (Abarca-Gómez et al., 2017; Guthold et al., 2018). In the USA, these health issues are particularly prevalent in minority and low-income populations (Du et al., 2019; Hales et al., 2017; Wang et al., 2020; Williams et al., 2018). Furthermore, numerous studies have found that physical activity...
declines as people age (Du et al., 2019). Given the significant health impacts from obesity and physical inactivity, addressing this issue in low-income, minority populations is imperative (Rezende et al., 2018; Wahid et al., 2016; White et al., 2017). Recent reports highlight the need to address the historically high obesity rates in the USA, in part through improvements in the built environment (Lustig and Cabrera, 2019; Warren et al., 2019). Design interventions to address obesity rates include infrastructure to support walking, cycling and use of public transit, as well as land use changes to increase residential density, integrate mixed land uses and enhance park access (Lustig and Cabrera, 2019). The built environment not only affects proximate behaviors and outcomes such as physical activity and obesity, it also has significant downstream effects. At a time when COVID-19 infection and mortality rates are disproportionately higher among African Americans and Latinos in the USA (Ray, 2020), the downstream effects of inadequate built environments are particularly evident. Ray (2020) emphasizes the structural roots of health disparities that have resulted in disproportionately poorer health outcomes in African American communities, in part related to the built environment (Ray, 2020). The need for improvements in the built environment in disadvantaged neighborhoods is clear. Research to illuminate ways in which urban planners and policy makers can create the greatest benefit from such improvements and investments is needed.

1.1. Built environment and health

Studies of the built environment have identified features and attributes of neighborhoods that may confer health benefits to residents, though relatively few of those studies have focused on disadvantaged populations. Recently, Smith et al. (2017) reviewed studies of the built environment and self-reported or objectively measured physical activity (PA), finding associations between activity and features such as walkability, presence of parks and infrastructure supportive of active transport. Few of the studies reviewed considered socioeconomic status or race-ethnicity, though two such studies found some evidence that disadvantaged individuals were less likely to use improved parks and new walking and cycling paths (Smith et al., 2017). Lovasi et al. (2009) reviewed studies of the built environment, obesity, and obesity-related health behaviors among individuals of low socioeconomic status, black race, or Hispanic ethnicity. In the studies reviewed, subjective and objective assessments of the built environment included features such as presence of fast food restaurants, walkability, and environmental disorder. Findings across studies were somewhat inconsistent, though several environmental characteristics appear more likely to improve obesity among disadvantaged populations, namely, access to healthy foods and places to exercise, and perceived safety (Lovasi et al., 2009). Casagrande et al. (2009) also reviewed studies of the built environment, focusing on self-reported physical activity, diet, and obesity or body mass index (BMI) among African Americans. In the studies that investigated physical activity or BMI as outcomes, exposures included participants’ assessments of built environmental features such as traffic, presence of sidewalks, street lighting at night, distance to destinations and perceived safety. Several studies in the review found light traffic, sidewalks, and safety from crime were associated with physical activity. One study found higher BMI among individuals who reported barriers to physical activity (Casagrande et al., 2009).

Several recent natural experiments have examined how changes to the built environment influence health focusing specifically on African American adults and low-income racial and ethnic minorities. A longitudinal assessment of the built environment, physical activity, BMI and neighborhood satisfaction was conducted in two low-income, African American communities in Pittsburgh, PA, USA, which are the primary focus of this study (Oubowitz et al., 2019). A natural experimental design was used to track participants’ activity, BMI, and neighborhood satisfaction before and after one of the neighborhoods received investments that improved the built environment, such as new residential buildings, sidewalks, and street crossings. However, physical activity and BMI were not found to be significantly different between participants living in the intervention and comparison neighborhoods. Gustat et al. (2012) conducted a natural experiment in a low-income, African American neighborhood in New Orleans, Louisiana, USA. A walking path and a new school playground designed to increase physical activity were installed in one neighborhood. Before and after the installation, self-reported physical activity of adult household members and observed physical activity were collected in the intervention neighborhood and two comparison neighborhoods. Observed activity increased in the intervention neighborhood and decreased in the comparison neighborhoods after the improvements were made. This finding was consistent with the theory that improvements in the built environment in a specific location would impact activity in the neighborhood overall (Gustat et al., 2012).

Two recent observational studies evaluated multiple measures of the built and social environment in disadvantaged urban neighborhoods. A study of African American adults and older adults living in urban areas of Detroit, MI (Gothe, 2018), investigated social and physical attributes associated with physical activity, measured using self-report and objective data (accelerometry). Physical activity was associated with self-efficacy but not with subjective perceptions of the environment such as accessibility, walkability, aesthetics, and crime. However, in focus groups, study participants reported that crime and access to places to exercise were barriers to physical activity (Gothe, 2018). Tung et al. (2016) studied perceived access to nearby health-enabling resources and objectively measured BMI in a high poverty urban setting in Chicago, IL, USA. Distance and travel time to the nearest health-promoting resource and nearest utilized resource were included in models predicting BMI. Participant BMI was positively associated with travel time to the utilized grocery store. Bypassing grocery stores nearer to home resulted in longer travel time or distance, both of which were associated with higher BMI (Tung et al., 2016).

Across these studies that focused on disadvantaged populations, patterns of associations between physical activity, BMI and the built environment emerge, though findings are inconsistent in part because the studies used different study designs and approaches to measure the built environment. The studies identify benefits of health promoting neighborhood features on health and provide information about how residents of disadvantaged neighborhoods use and interact with their environments in ways that can affect health. Overall, the presence of infrastructure supportive of active transport, places to exercise and perceived safety were associated with physical activity while perceived barriers to activity and longer distances or travel time to access healthy food were associated with higher BMI.
1.2. Measuring the built environment

Studies of the built environment have used various methods to obtain data on physical features and attributes that are linked to health-related behaviors and health outcomes. Micro-scale audits of the street environment have been conducted using Google Street View (GSV) and direct observation to collect data on the presence of sidewalks, aesthetic features such as gardens, and signs of neighborhood disorder (Bader et al., 2015; Badland et al., 2010; Rzotkiewicz et al., 2018). Spatial databases with macro-scale data such as land use, often manipulated within a geographic information system (GIS), are another common and important source of built environment data (Brownson et al., 2009). Subjective assessments of environmental conditions by study participants have also been used, for instance to capture features related to perceived walkability (Hajna et al., 2013; Nehme et al., 2016).

Each audit method has advantages and disadvantages. Google Street View (GSV) is a publicly-available source of environmental data that includes micro-scale features (Steinmetz-Wood et al., 2019). GSV is popular in studies of the built environment (Nguyen et al., 2019) and has established reliability and validity (Badland et al., 2010; Grew et al., 2013). Yet GSV images may not be time-sensitive, image quality can vary across locations (Rzotkiewicz et al., 2018), and imagery from different dates may be combined in GSV representations of places (Curtis et al., 2013). Direct observation provides objective assessments of neighborhood environments but requires coding environmental features in person at the time of observation which is costly (Bader et al., 2015). And inter-rater reliability for direct observation requires that two or more individuals evaluate the same environments contemporaneously. Macro-scale data such as from the U.S. Census or the National Land Cover Database (NLCD) (Homer et al., 2007) are reliable and publicly available and can be linked to places using various geographic scales, but the data may not be not time-sensitive and do not include micro-scale features associated with health promoting behaviors such as physical activity (Boarnet et al., 2011). Although subjective assessments of the built environment may be convenient, less expensive to obtain, and time-sensitive, objective measures may be stronger predictors of physical activity (Lin and Moudon, 2010; Zhang et al., 2019).

This study used GigaPan® technology to obtain images of the built environment. GigaPan® is a robotic system that stitches together numerous high-resolution images derived from a camera housed within the GigaPan® apparatus to create highly detailed, navigable, panoramic images (http://gigapan.com). GigaPan® offers several advantages as compared to other audit methods. The contextual information and high-resolution detail captured with GigaPan® technology are relevant in studies of the built environment. Images can be coded, and inter-rater reliability can be estimated as time permits, providing flexibility to collect time-sensitive data. Although GigaPan® technology requires taking photographs in the study setting, it provides an alternative to direct observation and GSV for capturing high-resolution, time-sensitive environmental imagery. Research to validate new audit technologies such as GigaPan® for use in studies of the built environment is needed (Badland et al., 2010).

The purpose of this study was to determine whether neighborhood environmental exposures were associated with physical activity and BMI in a longitudinal sample of disadvantaged, mostly African American adults in Pittsburgh, Pennsylvania, USA. In particular, we were interested in whether built environment characteristics derived from GigaPan® images could serve as valid predictors of physical activity and BMI. This study builds on the Pittsburgh Hill/Homewood Research on Neighborhood Change and Health (PHRESH) study of the Hill District and Homewood neighborhoods in Pittsburgh, which are low-income, predominantly African American communities. The PHRESH study was designed to evaluate the health of residents following planned changes to the built environment, including introduction of a full-service supermarket in the Hill District neighborhood, and renovation of parks and playgrounds and housing construction and developments (Dubowitz et al. 2015, 2019). A primary aim of the original PHRESH research was to collect data on food shopping in order to evaluate the influence of access to healthy affordable foods on diet, which may influence obesity and diet-related chronic diseases (Dubowitz et al., 2014). Both the Hill District and Homewood neighborhoods are geographically isolated from adjacent neighborhoods, primarily by natural features (elevation) and both neighborhoods lacked a full-service supermarket at the start of the PHRESH study (Dubowitz et al., 2015). In addition, the population in the Hill District and Homewood neighborhoods has declined significantly over time.¹ Master plans developed with input from community residents include goals such as protection of long-term and low-income residents, cultural preservation and provision of improved transportation networks (Homewood Comprehensive Community Plan, 2019) (The Greater Hill District Master Plan, 2011).

A prior study of the validity of individual measures of environmental features along street segments in the Hill District and Homewood neighborhoods, coded from GigaPan®, GSV and direct observation, found good agreement between the methods (Twardzik et al., 2018). Inter-rater reliability was also demonstrated for features in parks coded from GigaPan® images (Nelson et al., 2019). In this study we tested the predictive validity of environmental features of street segments coded from GigaPan® images in models predicting BMI, self-reported walking and moderate to vigorous physical activity (MVPA).²

2. Methods

Environmental audit data for this study were generated from GigaPan® images of street segments collected in 2015 in the Hill District and Homewood neighborhoods in Pittsburgh, Pennsylvania, USA. Audit data were coded during 2016–2017 and analyzed during 2018. In brief, the analysis involved summarizing the data based on conceptual categories, estimating inter-rater reliability of

---

¹ In 2010, the population in the Hill District was 10,450 (land area, 3.9 km²) and 6452 in Homewood (land area, 2.7 km²). In 2000, the Hill District population was 11,853 and the Homewood population was 9283 (PGH SNAP Census Data, 2016).

² Moderate-to-vigorous physical activity (MVPA) can include brisk walking, gardening, running, cycling, and competitive sports among other activities with similar intensities.
the summarized items and two individual items using a subsample of the data, and creating participant-level environmental exposures. Factor analysis was used to reduce the number of participant-level environmental exposures included in the final analysis. Similar methods have been used in studies of the built environment to reduce data into conceptually meaningful representations of environmental factors relevant to health (Adams et al., 2011, 2015; Feuillet et al., 2016). Regression analysis was used to test associations between the participant-level environmental exposures and three health measures – objectively measured BMI, self-reported frequency of walking and objectively measured MVPA – while controlling for baseline health and demographic variables. Stata version 14.2 was used for all analyses. This study was reviewed by the University of Michigan Institutional Review Board and deemed exempt.

2.1. Sample

2.1.1. Study participants

Households in the Hill District and Homewood neighborhoods were randomly selected from a list of all occupied residential addresses in the neighborhoods. Households in the Hill District closest to the site of a planned full-service grocery store were oversampled in keeping with the aims of the original study, which focused on shopping habits of households and the effect of a new full-service supermarket on diet. Eligibility criteria for the PHRESH study included being the primary food shopper and being at least 18 years old. Of the 1649 households who were reached at home and eligible to participate, 87% consented to participate in the PHRESH study. Participants were followed over time, with complete interview and accelerometer data obtained from 1003 participants in 2013 and from 676 of the same participants in 2016 (Dubowitz et al., 2015, 2019). This study utilizes data collected in 2013 and 2016, when accelerometer data were collected. Participants included in this study had baseline (2013) and follow-up (2016) interview data, were living in the Hill District or Homewood neighborhood in 2016, and had valid GigaPan® image data for street segments near their homes (n = 609; Hill District n = 433, Homewood n = 176).

2.1.2. Street environments

The street environment sample consisted of a random sample of 614 street segments, identified from ESRI and local government shapefiles, representing 25% of the street segments in the Hill District and Homewood neighborhoods. A street segment was defined as a block-face, from intersection to intersection. Street-level observations were conducted during the fall season in 2015 with GigaPan® technology. Trained observers in Pittsburgh obtained images of street environments using a protocol that involved setting up the GigaPan® apparatus on a tripod, aiming the camera to select the corners of the panoramic photo and initiating the GigaPan® to take the photographs. Photos were taken at the midpoint of each street block. Street segment data were collected prior to the follow-up in-home participant survey. Trained staff in Pittsburgh used software provided by GigaPan® to electronically stitch individual images together to create high-resolution panoramic images of the street environments. Many of the data collectors and some members of the study team in Pittsburgh were residents of the neighborhoods studied (Dubowitz et al., 2015). GigaPan® images were obtained for 590 of the street segments.

The stitched images were transferred via a secure server to our remote research team for auditing. Trained coders audited the images for environmental attributes including land use, traffic and pedestrian features, amenities and litter using a modified version of the Bridging the Gap (BTG) Street Segment Observation Form (Zenk et al., 2014). Coders’ training included reading a manual with detailed information on the audit form, participating in group discussions, and receiving instruction in navigating GigaPan® imagery and using a digital version of the BTG form. All coders achieved at least 80% reliability on a test sample of street segments (Twardzik et al., 2018). A total of 109 GigaPan® images were excluded from this study due to problems such as a mismatch between the GigaPan® image and GSV image, poor image quality, or problems with the image file, resulting in an analysis sample of 481 street segments (Hill District n = 177, Homewood n = 304). A random sample of 24% of the GigaPan® audits (n = 115) were double coded to create a set of data appropriate for estimating inter-rater reliability.

2.2. Measures

2.2.1. Participant characteristics, BMI, walking and MVPA

Participant characteristics including age, sex, race, and residential neighborhood were collected during in-person interviews conducted by trained staff in Pittsburgh. Signed informed consent was obtained by the interviewer at the time of the interview. Race was recoded as Black or Other (Other includes Asian, multi-racial, White and other race). Data on BMI, walking, and MVPA were collected at the baseline (2013) and follow-up (2016) time points. Objectively measured BMI was estimated from interviewer-measured height and weight collected by trained staff during the baseline and follow-up interviews. Walking was determined from a survey item that asked participants, “In the past month, how often did you walk to places in the neighborhood?” with responses coded on a six-point ordinal scale ranging from 0 (never) to 5 (at least once a day). MVPA was obtained from tri-axial Actigraph GT3X+ accelerometers worn on the non-dominant wrist for seven consecutive days (24 h per day). The data were transferred from GT3X format to raw CSV format and were processed during 2016 and 2017 using the GGIR v. 1.5–2 package in R v. 3.3.3 to obtain MVPA in minutes per day (Richardson et al., 2017; van Hees et al. 2014, 2015, 2019). The average MVPA per day was estimated from daily MVPA for participants with at least four days of valid wear time (accelerometer was worn for at least 10 h per day).

2.2.2. Environmental exposures

Coders conducting environmental audits evaluated 54 environmental attributes for each street segment sampled in the neighborhood on topics including land use type, traffic and pedestrian features, safety signs, amenities, and litter. Some attributes, such as...
light rail, did not appear in any of the audited images and were excluded. Conceptually similar items were combined by averaging or summing to create 12 summary measures. Two environmental features – street type and slope – were retained as individual items, resulting in a total of 14 street segment measures. Details on the coding and construction of these measures are provided in Appendix Table 1. For each participant, a 0.4 km (0.25 mile) road network buffer was created using the participant address as the centroid of the buffer (Richardson et al., 2017). The use of a 0.4 km radial buffer around the residential address is supported by prior research. Specifically, McMillan (2010) tested street segment sampling protocols in low-income urban areas with relatively higher minority populations finding that sampling 25% of street segments in a 0.4 km radial buffer provided an adequate representation of the residential walking environment (McMillan et al., 2010). In addition, a recent review of studies of the built environment and physical activity found that 0.4–0.5 km radial buffers were most commonly used (Barnett et al., 2017).

Each of the 14 street segment measures described above were summarized at the participant level to create 14 environmental exposure variables for use in further analysis, as follows. For each street segment within a participant buffer, each of the 14 street segment measures was weighted by the length of the segment divided by the total length of all street segments in the buffer. The 14 weighted measures were averaged across all segments in a buffer to construct 14 participant-level measures of environmental exposures. Thus, for each exposure (e.g., presence of a traffic light), the values for all sampled streets within a participant’s buffer were combined into a single value for the participant. Factor analysis was then used to reduce the 14 environmental exposures to three variables which were defined, based on item content, as factor 1, pedestrian-bicycle-amenities; factor 2, hilly-vacant-boarded; factor 3, PA-recreation/low housing density (full details in result section).

The factor analysis was conducted using all available data for the sample of participants who were living in the Hill District or Homewood neighborhood in 2016 and who had GigaPan® audit data for street segments in their residential buffer (n = 731). Participants with GigaPan® audit data for less than 10% of the total street length in the buffer were excluded (n = 41), resulting in an analysis sample of 690 participants (Hill District n = 476, Homewood n = 214). The average proportion of GigaPan® audited street length ranged from 0.1 to 0.6 (M = 0.29, SD = 0.1) and the average audited length ranged from 0.3 to 4.3 km (M = 1.8, SD = 0.9) for participant buffers included in the factor analysis.

2.3. Statistical analysis

2.3.1. Street segment measures: inter-rater reliability

Data included in the inter-rater reliability analysis were obtained for a random sample of 115 double-coded street segments audited by two raters. Inter-rater reliability was estimated for the 14 street segment level measures (12 summary measures and two individual items). Inter-rater reliability was estimated for continuous measures using intra-class correlations (ICCs) from two-way analysis of variance with mixed effects (Shrout and Fleiss, 1979). Cohen’s kappa (κ) was used to estimate inter-rater reliability for categorical items (Landis and Koch, 1977).

2.3.2. Participant level environmental exposures: factor analysis

The 14 participant-level environmental exposures were included in an exploratory factor analysis as a data reduction step. Factor analysis provides a way to summarize environmental exposures across a set of correlated measures and produces a smaller number of variables representing interrelated items. The principal factor method and orthogonal rotation were used. Predicted scores for factors with eigenvalues greater than one were estimated to obtain participant-level environmental exposure factors for use in regression analysis.

2.3.3. Regression analysis

Linear regression models were estimated predicting each health outcome at follow-up with the corresponding baseline health measure, environmental exposure factors, and demographic characteristics (sex, race, age, and neighborhood) as predictors. Logistic regression was used to predict dichotomous versions of the walking and MVPA outcomes as a complementary analysis.

3. Results

3.1. Participant characteristics

Summary statistics for participants’ demographic characteristics and environmental exposures are presented in Table 1. Sample sizes across outcomes differ due to missing data. More than three-quarters of the participants were female and over 90% were of Black race. On average participants were about 60 years old. Average BMI was higher at baseline than at follow-up, walking showed little change over time, and MVPA decreased.

3.2. Inter-rater reliability of street segment audit data

The inter-rater reliability estimates are presented in Table 2. Estimates were highest for street type, pedestrian and bicycle street features, walkability, amenities, and transit features, and were lowest for public communal/recreation space and PA venue.
3.3. Factor analysis of participants’ environmental exposures

The factor analysis of participants’ environmental exposures resulted in three factors with eigenvalues greater than 1.0, which explained 83.2% of the variance in the set of variables (Table 3). Factor 1 had high loadings for pedestrian and bicycle features, walkability, and amenities and transit facilities. Factor 2 had high positive loadings for slope, vacant lots and buildings, and buildings with broken or boarded windows, and a negative loading on aesthetics. Factor 3 had high positive loadings for PA venue and public communal/recreation space, and a negative loading for housing density and variety. Labels assigned to the factors to represent their substantive content were based on the strongest factor loadings as follows: factor 1, pedestrian-bicycle-amenities; factor 2, hilly-vacant-boarded; factor 3, PA-recreation/low housing density.

3.4. Comparison of included and excluded participants

Participants included in each analysis sample were compared with excluded participants on demographic characteristics and environmental exposure factors using t-tests. Excluded participants were younger on average than participants included in the BMI sample ($t = -2.9, p = 0.004$) and the walking sample ($t = -3.1, p = 0.002$). Participants in the MVPA sample did not differ from excluded participants on any of the demographic measures. Excluded participants did not differ significantly from included participants on any of the environmental exposures in any of the analysis samples.

3.5. Regression analysis

Results of the linear regressions predicting BMI, walking and MVPA are presented in Table 4. All models included the three environmental exposures (pedestrian-bicycle amenities, hilly-vacant-boarded, PA-recreation/low housing density) as predictors and controlled for demographic variables and baseline BMI, walking or MVPA as appropriate. In all models tested, the baseline health...
measure was significantly positively associated with the corresponding follow-up health measure, and age was significantly negatively associated with the health outcome. BMI at follow-up was negatively associated with the pedestrian-bicycle-amenities factor ($B = -0.47, p = 0.02$); BMI was lower when the infrastructure was more supportive of walking and bicycling. Walking and MVPA were not significantly associated with any of the environmental exposures (pedestrian-bicycle-amenities, hilly-vacant-boarded, PA-recreation/low housing density) in the models tested.

Missing data reduced the walking and MVPA analysis samples as compared to the BMI sample, and the walking and MVPA distributions were skewed due to low levels of physical activity among participants. To address the possible impact of skew, we conducted a complementary analysis using logistic regression to predict dichotomized versions of walking and MVPA, controlling for the corresponding baseline health measure and demographics. About half of the respondents reported walking three or more times per week in the neighborhood at baseline (50%) and follow-up (48%), so walking was dichotomized as “less than 3 times a week” versus “3 or more times a week.” Over half of the participants had no MVPA at baseline (61%) or follow-up (58%), so we dichotomized MVPA as

Table 3
Factor analysis of participants’ environmental exposures ($n = 690$).

| Variable                        | Pedestrian-bicycle-amenities | Hilly-vacant-boarded | PA-recreation/low housing density |
|---------------------------------|------------------------------|----------------------|----------------------------------|
| Housing                         | -0.02                        | 0.14                 | -0.58                            |
| Office                          | 0.49                         | 0.11                 | 0.10                             |
| Service/retail                  | 0.07                         | 0.02                 | 0.05                             |
| Public communal/recreation      | 0.39                         | -0.18                | 0.50                             |
| Vacant-boarded buildings        | -0.20                        | 0.66                 | -0.30                            |
| Physical activity venue         | 0.18                         | -0.08                | 0.68                             |
| Street trees & shade            | 0.05                         | -0.04                | -0.03                            |
| Street type (through-street)    | -0.15                        | 0.10                 | 0.14                             |
| Pedestrian and bicycle features | 0.95                         | 0.04                 | 0.10                             |
| Aesthetics                      | 0.20                         | -0.47                | -0.23                            |
| Amenities and transit facilities| 0.59                         | 0.18                 | 0.00                             |
| Trash and safety               | -0.34                        | -0.04                | -0.15                            |
| Walkability                     | 0.92                         | -0.10                | 0.05                             |
| Slope                           | 0.15                         | 0.78                 | -0.05                            |
| % Variance explained           | 3.49                         | 1.91                 | 1.31                             |
| PA, physical activity.          |                              |                      |                                  |

Table 4
Linear regression models predicting health outcomes at follow-up.

| Variables                               | B (95% CI)   | t    | p     | F (df)   | $R^2$ |
|-----------------------------------------|--------------|------|-------|----------|-------|
| BMI                                     |              |      |       |          |       |
| Baseline BMI                            | 0.89 (0.85, 0.94) | 38.8 | <.001 |          | 0.74  |
| Pedestrian-bicycle-amenities             | -0.47 (-0.85, -0.09) | -2.4 | 0.02  |          |       |
| Hilly-vacant-boarded                    | -0.30 (-0.82, 0.21) | -1.2 | 0.25  |          |       |
| PA-recreation/low housing density       | -0.06 (-0.48, 0.37) | -0.3 | 0.79  |          |       |
| Homewood                                | -0.50 (-1.53, 0.54) | -1.0 | 0.34  |          |       |
| Female                                  | 0.26 (-0.56, 1.07)  | 0.6  | 0.54  |          |       |
| Black race                              | 0.67 (-0.55, 1.88)  | 1.1  | 0.28  |          |       |
| Age                                     | -0.02 (-0.05, -0.002) | -2.1 | 0.03  |          |       |
| Walking                                 |              |      |       |          | 0.18  |
| Baseline walking                        | 0.36 (0.28, 0.44)  | 9.2  | <.001 |          |       |
| Pedestrian-bicycle-amenities             | 0.13 (-0.03, 0.29)  | 1.6  | 0.11  |          |       |
| Hilly-vacant-boarded                    | 0.18 (-0.03, -0.39) | 1.7  | 0.08  |          |       |
| PA-recreation/low housing density       | -0.14 (-0.32, 0.04) | -1.6 | 0.12  |          |       |
| Homewood                                | 0.32 (-0.11, 0.76)  | 1.5  | 0.15  |          |       |
| Female                                  | -0.25 (-0.57, 0.08) | -1.5 | 0.14  |          |       |
| Black race                              | -0.19 (-0.69, 0.32) | -0.7 | 0.46  |          |       |
| Age                                     | -0.02 (-0.02, -0.01) | -3.3 | <.001 |          |       |
| MVPA                                    |              |      |       |          | 0.24  |
| Baseline MVPA                           | 0.29 (0.24, 0.35)  | 10.7 | <.001 |          |       |
| Pedestrian-bicycle-amenities             | -0.004 (-1.05, 1.05) | -0.01 | 0.99  |          |       |
| Hilly-vacant-boarded                    | 0.79 (-0.66, 2.25)  | 1.1  | 0.29  |          |       |
| PA-recreation/low housing density       | 0.23 (-0.94, 1.39)  | 0.4  | 0.70  |          |       |
| Homewood                                | 0.48 (2.44, 3.41)   | 0.3  | 0.75  |          |       |
| Female                                  | -0.81 (-3.26, 1.64) | -0.7 | 0.52  |          |       |
| Black race                              | -0.30 (-3.68, 3.08) | -0.2 | 0.86  |          |       |
| Age                                     | -0.09 (-0.16, -0.03) | -2.9 | <.001 |          |       |

B, unstandardized regression coefficient; BMI, body mass index; PA, physical activity; MVPA, moderate to vigorous physical activity.
“none” versus “some.”

The likelihood of walking in the neighborhood three or more times a week was lower when PA-recreation/low housing density exposure was higher (odds ratio = 0.73, 95% confidence interval, 0.57, 0.94). In the model predicting any MVPA, none of the environmental exposure factors were significant. Full results of the complementary analysis are provided in Appendix Table 2.

4. Discussion

The purpose of this study was to determine whether environmental audit data derived from GigaPan® imagery could be used to predict health outcomes including BMI, walking and MVPA in a longitudinal sample of adults in two low-income, primarily African American neighborhoods in Pittsburgh, PA, USA. An inter-rater reliability analysis showed moderate to substantial agreement among raters on most of the environmental audit measures. Three factors representing study participants’ environmental exposures were derived from the audit data and tested for predictive validity in regression models. The pedestrian-bicycle-amenities and PA-recreation/low housing density factors were significantly associated with health outcomes in models predicting BMI and walking, respectively. The environmental exposures were not significantly associated with MVPA, and the hilly-vacant-boarded factor was not a significant predictor of health, in any of the models tested.

The pedestrian-bicycle-amenities factor was negatively associated with BMI. This finding was in the expected direction and supports the use of GigaPan® imagery in studies of the built environment and health. The pedestrian-bicycle-amenities factor captured features such as sidewalks, curbs, marked crossings, stop signs at pedestrian crossings, and amenities such as benches at transit stops. In comparison, prior studies of disadvantaged neighborhoods found perceived barriers to physical activity associated with higher BMI (Casagrande et al., 2009), as well as no association between infrastructure supportive of activity and BMI (Tung et al., 2016). Those studies reported associations between subjective assessments or macro-scale data on distance to a nearby resource, whereas our study used micro-scale audits of environmental features. Dubowitz et al. (2019) found no significant difference in BMI between residents in the Hill and Homewood neighborhoods, though unlike our study that analysis did not include micro-scale data on the environment (Dubowitz et al., 2019).

Participants in this study who value healthy lifestyles may have chosen to live in areas that support their desire to live a healthy lifestyle, which could explain in part the finding of lower BMI. Numerous studies have discussed and examined whether self-selection bias drives the relationship between the built environment, health and health-related behavior, such as BMI and physical activity (Cao et al., 2009; Diez Roux, 2004; McCormack and Shiell, 2011). This spurious association could arise when people who value healthy lifestyles chose to live in areas with environments supportive of such lifestyle. Studies that have examined the degree to which self-selection explains the association between the built environment and behavior have had mixed results, though most studies find little to modest effects of self-selection (Cao et al., 2009; Frank et al., 2007; Sallis et al., 2009). A review of studies that utilized designs that help address self-selection suggested a mix of associations in the expected direction and null associations (McCormack and Shiell, 2011). Our study utilized a longitudinal design to examine the association of the built environment on change in physical activity and BMI over time, which is an advance over the large body of cross-sectional studies exploring this relationship in the literature (Haselwandter et al., 2015; Papas et al., 2007). Furthermore, our population was sampled from two low-income communities. It is speculated that self-selection bias could be less in low-income communities where people may not have the luxury of choosing neighborhoods specifically for environments supportive of healthy lifestyles (Wang and Cao, 2017; Zang et al., 2019). However, self-selection can still result in bias in this case. This can occur if low-income persons choose neighborhoods based on specific characteristics that are associated with environments not supportive of health, such as low housing costs, and if low-income is associated with the outcome of interest (Boone-Heinonen et al., 2011). Thus, while our longitudinal design and study population make it less likely that the results are due to self-selection bias, this possibility cannot be ruled out.

A model predicting walking as a continuous variable did not show significant associations with the environmental exposure factors. Dubowitz et al. (2019) also found no difference in walking behavior between the Hill and Homewood populations though, as noted earlier, that analysis did not include micro-scale built environment data (Dubowitz et al., 2019). In a complementary analysis, we found that a dichotomous measure of frequent walking was negatively associated with the PA-recreation/low housing density factor. This finding conflicts with recent studies that have shown positive effects of recreational facilities on all types of walking. For instance, self-reported presence of recreational facilities was associated with self-reported walking in a sample of adults (Cao et al., 2009; Diez Roux, 2004; McCormack and Shiell, 2011). This spurious association could arise when people who value healthy lifestyles chose to live in areas with environments supportive of such lifestyle. Studies that have examined the degree to which self-selection explains the association between the built environment and behavior have had mixed results, though most studies find little to modest effects of self-selection (Cao et al., 2009; Diez Roux, 2004; McCormack and Shiell, 2011). This spurious association could arise when people who value healthy lifestyles chose to live in areas with environments supportive of such lifestyle. Studies that have examined the degree to which self-selection explains the association between the built environment and behavior have had mixed results, though most studies find little to modest effects of self-selection (Cao et al., 2009; Frank et al., 2007; Sallis et al., 2009). A review of studies that utilized designs that help address self-selection suggested a mix of associations in the expected direction and null associations (McCormack and Shiell, 2011). Our study utilized a longitudinal design to examine the association of the built environment on change in physical activity and BMI over time, which is an advance over the large body of cross-sectional studies exploring this relationship in the literature (Haselwandter et al., 2015; Papas et al., 2007). Furthermore, our population was sampled from two low-income communities. It is speculated that self-selection bias could be less in low-income communities where people may not have the luxury of choosing neighborhoods specifically for environments supportive of healthy lifestyles (Wang and Cao, 2017; Zang et al., 2019). However, self-selection can still result in bias in this case. This can occur if low-income persons choose neighborhoods based on specific characteristics that are associated with environments not supportive of health, such as low housing costs, and if low-income is associated with the outcome of interest (Boone-Heinonen et al., 2011). Thus, while our longitudinal design and study population make it less likely that the results are due to self-selection bias, this possibility cannot be ruled out.

A model predicting walking as a continuous variable did not show significant associations with the environmental exposure factors. Dubowitz et al. (2019) also found no difference in walking behavior between the Hill and Homewood populations though, as noted earlier, that analysis did not include micro-scale built environment data (Dubowitz et al., 2019). In a complementary analysis, we found that a dichotomous measure of frequent walking was negatively associated with the PA-recreation/low housing density factor. This finding conflicts with recent studies that have shown positive effects of recreational facilities on all types of walking. For instance, self-reported presence of recreational facilities was associated with self-reported walking in a sample of adults (Cao et al., 2009; Diez Roux, 2004; McCormack and Shiell, 2011). This spurious association could arise when people who value healthy lifestyles chose to live in areas with environments supportive of such lifestyle. Studies that have examined the degree to which self-selection explains the association between the built environment and behavior have had mixed results, though most studies find little to modest effects of self-selection (Cao et al., 2009; Frank et al., 2007; Sallis et al., 2009). A review of studies that utilized designs that help address self-selection suggested a mix of associations in the expected direction and null associations (McCormack and Shiell, 2011). Our study utilized a longitudinal design to examine the association of the built environment on change in physical activity and BMI over time, which is an advance over the large body of cross-sectional studies exploring this relationship in the literature (Haselwandter et al., 2015; Papas et al., 2007). Furthermore, our population was sampled from two low-income communities. It is speculated that self-selection bias could be less in low-income communities where people may not have the luxury of choosing neighborhoods specifically for environments supportive of healthy lifestyles (Wang and Cao, 2017; Zang et al., 2019). However, self-selection can still result in bias in this case. This can occur if low-income persons choose neighborhoods based on specific characteristics that are associated with environments not supportive of health, such as low housing costs, and if low-income is associated with the outcome of interest (Boone-Heinonen et al., 2011). Thus, while our longitudinal design and study population make it less likely that the results are due to self-selection bias, this possibility cannot be ruled out.

A model predicting walking as a continuous variable did not show significant associations with the environmental exposure factors. Dubowitz et al. (2019) also found no difference in walking behavior between the Hill and Homewood populations though, as noted earlier, that analysis did not include micro-scale built environment data (Dubowitz et al., 2019). In a complementary analysis, we found that a dichotomous measure of frequent walking was negatively associated with the PA-recreation/low housing density factor. This finding conflicts with recent studies that have shown positive effects of recreational facilities on all types of walking. For instance, self-reported presence of recreational facilities was associated with self-reported walking in a sample of adults (Cao et al., 2009; Diez Roux, 2004; McCormack and Shiell, 2011). This spurious association could arise when people who value healthy lifestyles chose to live in areas with environments supportive of such lifestyle. Studies that have examined the degree to which self-selection explains the association between the built environment and behavior have had mixed results, though most studies find little to modest effects of self-selection (Cao et al., 2009; Frank et al., 2007; Sallis et al., 2009). A review of studies that utilized designs that help address self-selection suggested a mix of associations in the expected direction and null associations (McCormack and Shiell, 2011). Our study utilized a longitudinal design to examine the association of the built environment on change in physical activity and BMI over time, which is an advance over the large body of cross-sectional studies exploring this relationship in the literature (Haselwandter et al., 2015; Papas et al., 2007). Furthermore, our population was sampled from two low-income communities. It is speculated that self-selection bias could be less in low-income communities where people may not have the luxury of choosing neighborhoods specifically for environments supportive of healthy lifestyles (Wang and Cao, 2017; Zang et al., 2019). However, self-selection can still result in bias in this case. This can occur if low-income persons choose neighborhoods based on specific characteristics that are associated with environments not supportive of health, such as low housing costs, and if low-income is associated with the outcome of interest (Boone-Heinonen et al., 2011). Thus, while our longitudinal design and study population make it less likely that the results are due to self-selection bias, this possibility cannot be ruled out.
have affected the association.

The environmental exposures were not significant in models predicting continuous or dichotomized MVPA. This result may be explained in part by the very low level of MVPA observed in this sample both at baseline and follow-up (Dubowitz et al., 2019). The MVPA measure may not have captured the type of physical activity that would likely occur within the 0.4 km network residential buffer near the home. Prior studies of residents of the Hill District and Homewood neighborhoods found no difference in MVPA in a comparison of the neighborhoods (Dubowitz et al., 2019), and no association between MVPA, walkability from in-person audit data, and GIS-based green space, though an association was found between walkability and MVPA in an analysis of women only (Richardson et al., 2017).

The environmental exposure related to the hilliness of the area, presence of vacant lots and vacant/boarded buildings was not associated with any of the health outcomes. Although the presence of vacant lots and vacant/boarded buildings might be associated with perceived safety or crime, we did not include crime and safety in this study. Other studies have found associations between physical activity, perceived safety and crime (Casagrande et al., 2009; Gothe, 2018; Lovasi et al., 2009). More research is needed to investigate possible associations between the presence of vacant lots and vacant/boarded buildings captured in micro-scale environmental audits, perceptions of safety, crime, and health outcomes.

Prior studies established the reliability and validity of built environment measures from GigaPan® images in comparison with GSV and direct observation (Nelson et al., 2019; Twardzik et al., 2018). This study further validates the use of GigaPan® in studies of the built environment and health by establishing predictive validity from the association between BMI and exposure to features in the environment that support walking and cycling. GigaPan® images can be retained and used for comparison with the same environments studied at a later point in time, thus GigaPan® technology may be useful for urban planning and policy making purposes, especially when micro-scale, time-sensitive data on the built environment are desired.

4.1. Limitations and strengths

Strengths of this study include a strong recruitment process and high recruitment rate for a population-based study in a low-income neighborhood (Dubowitz et al., 2015). Recruitment was likely facilitated by utilizing community members as part of the study team. Furthermore, those enrolled were generally demographically representative of the community. For example, based on Census data, the percentage of residents in the community who self-defined as black were 84% (Hill District) and 91% (Homewood), which is similar to the percent who self-defined as black in this study. In addition, the methods applied to construct measures of the environment captured micro-scale characteristics of the neighborhoods that are relevant for urban planning and policy making, particularly because small scale modifications can be implemented incrementally in neighborhood environments to enhance traffic safety and promote active transport (Brown et al., 2017).

Limitations of the study include that the homogeneous sample limits generalizability to other populations. Further, although the recruitment rate was high and the sample generally demographically representative of the community, the sample was slightly older than the community population, more likely to be female and less likely to have children. This is likely due to several reasons. The primary food shopper was selected for inclusion in the main study, likely resulting in a sample of mostly female, older respondents (Dubowitz et al., 2015). Another limitation is that this study sampled adults and street segments in two low-income neighborhoods in the same city. Other studies of the built environment and health in disadvantaged individuals in the U.S. have included more diverse samples from several cities (Casagrande et al., 2009; Lovasi et al., 2009). Finally, although the audit tool was both detailed and comprehensive, some social environment exposures were not included, such as crime and perceived safety, which have been shown to negatively influence physical activity (Casagrande et al., 2009; Lovasi et al., 2009; Nehme et al., 2016).

5. Conclusion

Predictive validity was demonstrated for an environmental exposure measure derived from GigaPan® imagery that captured features supportive of walking and cycling in a longitudinal model predicting BMI. A complementary analysis found a lower likelihood of frequent walking in the neighborhood among participants with exposure to more public communal space and recreational features, but fewer types and lower density of housing.

Author statement

Cathy Antonakos analyzed and interpreted the data, and drafted and revised the manuscript. Ross Baiers processed, analyzed and interpreted data and assisted with drafting and revision of the manuscript. Philippa Clarke assisted with critical revision of the manuscript. Natalie Colabianchi and Tamara Dubowitz conceptualized and designed the study, acquired data and assisted with critical revision of the manuscript.

Acknowledgments

This work was supported by grants from the National Cancer Institute (NCI), National Institutes of Health, Department of Health and Human Services (R21 CA188481, Natalie Colabianchi, PI and R01 CA164137, Tamara Dubowitz, PI). The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Cancer Institute or the National Institutes of Health. This research was also supported in part through computational resources and services provided by Advanced
### Table 1
Street segment audit data coding and descriptive statistics

| Variable | Scale coding | Mean (SD) |
|----------|--------------|-----------|
| Housing  | Average      | 0.41 (0.4) |
| Housing – detached | 0.70 (0.8) |
| Housing – attached | 0.21 (0.5) |
| Housing – apartments | 0.32 (0.6) |
| Office   | Average      | 0.04 (0.1) |
| Public/civic | 0.01 (0.1) |
| Office/professional | 0.004 (0.1) |
| Institutional | 0.10 (0.3) |
| Industrial/manufacturing | 0.02 (0.2) |
| Service/retail | Average | 0.09 (0.3) |
| Service   |              | 0.09 (0.3) |
| Retail    |              | 0.09 (0.3) |
| Public communal/recreation space | Average | 0.05 (0.2) |
| Public communal space | 0.01 (0.1) |
| Recreation/fitness | 0.09 (0.3) |
| Vacant-boarded | Average | 0.16 (0.3) |
| Vacant building or lot | 0.19 (0.4) |
| Broken/boarded windows | 0.14 (0.3) |
| Physical activity venue | Any present | 0.05 (0.2) |
| Indoor PA facility | 0.01 (0.1) |
| Park with sign, no equipment | 0.002 (0.05) |
| Park with exercise/sport facilities/equip | 0.01 (0.1) |
| Stand-alone playing court | 0.01 (0.1) |
| Stand-alone playing field | 0.01 (0.1) |
| School grounds | 0.02 (0.1) |
| Outdoor pool | 0.002 (0.05) |
| Off-road trail | 0.004 (0.06) |
| Street trees & shade | Average | 0.31 (0.5) |
| How many street trees? | 0.41 (0.7) |
| Do trees shade sidewalk? | 0.21 (0.5) |
| Street type (through street) | Single item | 0.95 (0.2) |
| Pedestrian and bicycle street features | Average | 0.27 (0.1) |
| Speed hump/table | 0.002 (0.05) |
| Median with traffic island | 0.03 (0.1) |
| Marked bike lane | 0.02 (0.2) |
| Bike lane separated by physical barrier | 0.002 (0.05) |
| Street shoulder | 0.02 (0.2) |
| Curb | 0.80 (0.4) |
| Street or sidewalk lighting | 0.89 (0.3) |
| Sidewalk | 0.81 (0.4) |
| Street and sidewalk buffer | 0.38 (0.5) |
| Continuous sidewalk | 0.89 (0.3) |
| Sidewalk continuous at both ends between segments | 0.65 (0.5) |
| Curb cuts or ramps missing at crossings | 0.70 (0.5) |
| Traffic light | 0.16 (0.4) |
| Pedestrian signal at traffic light | 0.05 (0.2) |
| Stop sign | 0.37 (0.5) |
| Marked crosswalk | 0.23 (0.4) |
| Bicycle crossing signage | 0.004 (0.1) |
| Other bicycle-related signage | 0.01 (0.1) |
| Pedestrian crossing signage | 0.03 (0.2) |
| Children at play/special population signage | 0.02 (0.1) |
| Special speed limit | 0.01 (0.1) |
| Aesthetics | Any present | 0.24 (0.4) |
| Neighborhood or community sign | 0.01 (0.1) |
| Garden, flower bed, or planter | 0.22 (0.4) |
| Art, statue, or monument | 0.03 (0.2) |
| Amenities and transit facilities | Any present | 0.20 (0.4) |
| Public trash can | 0.09 (0.3) |
| Benches or other seating | 0.004 (0.1) |
| Bicycle parking | 0.01 (0.1) |
| Bus stop | 0.15 (0.4) |
| Bench or covered shelter at transit | 0.03 (0.2) |

(continued on next page)
OR, Odds ratio; PA, physical activity.

References

Abarca-Gómez, L., et al., 2017. Worldwide trends in body-mass index, underweight, overweight, and obesity from 1975 to 2016: a pooled analysis of 2416 population-based measurement studies in 128·9 million children, adolescents, and adults. Lancet 390, 2627–2642. https://doi.org/10.1016/S0140-6736(17)32129-3.

Adams, M.A., et al., 2011. Neighborhood environment profiles related to physical activity and weight status: A latent profile analysis. Prev. Med. 52, 326–331. https://doi.org/10.1016/j.ypmed.2011.02.020.

Adams, M.A., Todd, M., Kurka, J., Conway, T.L., Cain, K.L., Frank, L.D., Sallis, J.F., 2015. Patterns of walkability, transit, and recreation environment for physical activity. Am. J. Prev. Med. 49, 878–887. https://doi.org/10.1016/j.amepre.2015.05.024.

Bader, M.D.M., Mooney, S.J., Lee, Y.J., Sheehan, D., Neckerman, K.M., Rundle, A.G., Teitler, J.O., 2015. Development and deployment of the computer assisted neighborhood visual assessment system (CANVAS) to measure health-related neighborhood conditions. Health Place 31, 163–172. https://doi.org/10.1016/j.healthplace.2014.10.012.

Badland, H.M., Opit, S., Witten, K., Kearns, R.A., Mavoa, S., 2010. Can virtual streetscape audits reliably replace physical streetscape audits? J. Urban Health 87, 1007–1016. https://doi.org/10.1007/s11524-010-9505-z.

Barnetti, D.W., Barnett, A., Nathan, A., Van Cauwenberg, J., Cerin, E., Council on, E., Physical Activity - Older Adults working g, 2017. Built environmental correlates of older adults’ total physical activity and walking: a systematic review and meta-analysis. Int. J. Behav. Nutr. Phys. Act. 14, 103. https://doi.org/10.1186/s12966-017-0558-z.

Boarnet, M.G., Forsyth, A., Day, K., Oakes, J.M., 2011. The Street Level Built Environment and Physical Activity and Walking: Results of a Predictive Validity Study for the Irvine Minnesota Inventory Environment and Behavior, vol. 43, pp. 735–775. https://doi.org/10.1177/0013916510379760.
Steinmetz-Wood, M., Velauthapillai, K., O'Brien, G., Ross, N.A., 2019. Assessing the micro-scale environment using Google street view: the virtual systematic tool for evaluating pedestrian streetscapes (Virtual-STEPS). BMC Publ. Health 19, 1246. https://doi.org/10.1186/s12889-019-7460-3.

The Greater Hill District Master Plan (2011).

Tung, E.L., Peck, M.E., Makelarski, J.A., Escamilla, V., Lindau, S.T., 2016. Adult BMI and access to built environment resources in a high-poverty, urban geography. Am. J. Prev. Med. 51, e119-e127. https://doi.org/10.1016/j.amepre.2016.04.019.

Twardzik, E., Antonakos, C., Baiers, R., Dubowitz, T., Clarke, P., Colabianchi, N., 2018. Validity of environmental audits using GigaPan® and Google earth technology. Int. J. Health Geogr. 17 https://doi.org/10.1186/s12942-018-0147-7.

van Hees, V.T., et al., 2014. Autocalibration of accelerometer data for free-living physical activity assessment using local gravity and temperature: an evaluation on four continents. J. Appl. Physiol. 117, 738–744. https://doi.org/10.1152/japplphysiol.00421.2014.

van Hees, V.T., et al., 2015. A novel, open access method to assess sleep duration using a wrist-worn accelerometer. PLoS One 10, e0142533. https://doi.org/10.1371/journal.pone.0142533.

van Hees, V., et al., 2019. G GIR. Zenodo. https://doi.org/10.5281/zenodo.1051064.

Wahid, A., et al., 2016. Quantifying the association between physical activity and cardiovascular disease and diabetes: a systematic review and meta-analysis. J. Am. Heart Assoc. 5, e002495 https://doi.org/10.1161/JAHA.115.002495.

Wang, D., Cao, X., 2017. Impacts of the built environment on activity-travel behavior: are there differences between public and private housing residents in Hong Kong? Transport. Res. Pol. Pract. 103, 25–35. https://doi.org/10.1016/j.trapa.2017.05.018.

Wang, Y., Beydoun, M.A., Min, J., Xue, H., Kaminsky, L.A., Cheskin, L.J., 2020. Has the prevalence of overweight, obesity and central obesity levelled off in the United States? Trends, patterns, disparities, and future projections for the obesity epidemic. Int. J. Epidemiol. https://doi.org/10.1093/ije/dyz273.

Warren, M, Beck, S, Delgado, D, 2019. The State of Obesity: Better Policies for a Healthier America 2019. Trust for America’s Health. https://www.tfah.org/report-details/stateofobesity2019/. (Accessed 4 May 2020).

White, R.L., Babic, M.J., Parker, P.D., Lubans, D.R., Astell-Burt, T., Lonsdale, C., 2017. Domain-specific physical activity and mental health: a meta-analysis. Am. J. Prev. Med. 52, 653–666. https://doi.org/10.1016/j.amepre.2016.12.008.

Williams, W.M., Yore, M.M., Whitt-Glover, M.C., 2018. Estimating physical activity trends among blacks in the United States through examination of four national surveys. AMI S Publ. Health 5, 144–157. https://doi.org/10.3934/publichealth.2018.2.144.

Yun, Y.H., 2019. Environmental factors associated with older adult’s walking behaviors: A Systematic Review of Quantitative Studies. Sustainability 11. https://doi.org/10.3390/su11123253.

Zang, P., Lu, Y., Mu, J., Xie, B., Wang, R., Liu, Y., 2019. Disentangling residential self-selection from impacts of built environment characteristics on travel behaviors for older adults. Soc. Sci. Med. 238, 112515. https://doi.org/10.1016/j.socscimed.2019.112515.

Zenk, S.N., Slater, S., Rashid, S., 2014. Collecting Contextual Health Survey Data Using Systematic Observation. In: Johnson, T (Ed.), Handbook of Health Survey Methods. Wiley & Sons, Hoboken, NJ, pp. 421–445.

Zhang, L., Zhou, S., Kwan, M.-P., 2019. A comparative analysis of the impacts of objective versus subjective neighborhood environment on physical, mental, and social health. Health Place 59, 102170. https://doi.org/10.1016/j.healthplace.2019.102170.