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Assessing greenspace and cardiovascular health through deep-learning analysis of street-view imagery in a cohort of US children

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AUTHOR CONTRIBUTIONS

Dr. Yi had full access to all the data in the study and took responsibility for the integrity of the data and accuracy of the data analysis.
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Acquisition, analysis, or interpretation of data: Yi, Rifas-Shiman, Aris, James.
Drafting of the manuscript: Yi, James.
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Declaration of interests

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

Abstract

Background: Accurately capturing individuals' experiences with greenspace at ground-level can provide valuable insights into their impact on children's health. However, most previous research has relied on coarse satellite-based measurements.

Methods: We utilized CVH and residential address data from Project Viva, a US-based pre-birth cohort, tracking participants from mid-childhood to late adolescence (2007–21). A deep learning segmentation algorithm was applied to street-view images across the US to estimate % street-view trees, grass, and other greenspace (flowers/field/plants). Exposure estimates were derived by inking street-view greenspace metrics to 500m of participants' residences during mid-childhood, early and late adolescence. CVH scores (range 0–100; higher indicate better CVH) were calculated using the American Heart Association's Life's Essential 8 algorithm at these three time points, incorporating four biomedical components (body weight, blood lipids, blood glucose, blood pressure) and four behavioral components (diet, physical activity, nicotine exposure, sleep). Linear regression models were used to examine cross-sectional and cumulative associations between street-view greenspace metrics and CVH scores. Generalized estimating equations models were used to examine associations between street-view greenspace metrics and changes in CVH scores across three timepoints. All models were adjusted for individual and neighborhood-level confounders.

Results: Adjusting for confounders, a one-SD increase in street-view trees within 500m of residence was cross-sectionally associated with a 1.92-point (95%CI: 0.50, 3.35) higher CVH score in late adolescence, but not mid-childhood or early adolescence. Longitudinally, street-view greenspace metrics at baseline (either mid-childhood or early adolescence) were not associated with changes in CVH scores at the same and all subsequent time points. Cumulative street-view greenspace metrics across the three time points were also not associated with CVH scores in late adolescence.

Conclusion and Relevance: In this US cohort of children, we observed few evidence of associations between street-level greenspace children's CVH, though the impact may vary with children's growth stage.

Keywords

Life's essential 8; Green space; Street-view imagery; Children and Adolescents; Deep learning algorithms; Environmental epidemiology

INTRODUCTION

Cardiovascular health (CVH) is an important aspect of health for children and adolescents.[1] According to the American Heart Association (AHA), CVH is a construct that combines behavioral factors (e.g., physical activity, diet) and biomedical factors (e.g., body weight, blood glucose).[1] Optimal CVH in children and adolescents has been associated with better CVH in adulthood,[2] which can lead to longer cardiovascular disease (CVD) free survival, higher overall life expectancy, and higher quality of life.[1,3] Greenspace may shape CVH in children and adolescents by influencing CVH-related behavioral pathways, including physical activity and sleep,[4–7] as well as benefiting mental health and psychological wellbeing.[8–10] Moreover, several observational studies have linked greater exposure greenspace to lower likelihood of overweight/obesity, lower blood glucose levels, and lower blood pressure in children and adolescents.[11–13] However, prior studies were measured only one or two components of CVH and used coarse satellite-based measures (e.g., the normalized difference vegetation index [NDVI]) around a residential address to capture greenspace exposure only at a single point in time.[13]

Although satellite-based NDVI is standardized across studies, it cannot distinguish between specific greenspace types such as trees, grass, or other types of vegetation, which may influence CVH through various behavioral, physiological, and psychological pathways.[14] For instance, trees can promote children's physical activity by providing shade and reducing exposure to environmental hazards like air pollution and noise.[15,16] Grass is often associated with public areas such as parks, essential for children's sports and social interactions.[17] Additionally, plants and flowers improve aesthetics, potentially enhancing children's mood and reducing stress.[18] Moreover, satellite-based measures are not capable of capturing a person's visual experience of greenspace at the street-level, which provides a more accurate representation of the actual environment experienced by individuals on a daily basis.[19] Recently, street-view-based measures have emerged to complement NDVI to examine relationships between individual greenspace components and some aspects of CVH.[5,16,20,21] However, few studies have examined street-view greenspace components on the components of CVH, and none of these studies have focused on children and applied a composite measure of CVH.

To address the limitations of prior research and improve methods for assessing greenspace exposure and CVH in children, we applied deep learning segmentation models to classify and quantify specific greenspace types from street-view images and examined their cross-sectional and longitudinal relationship to overall CVH at mid-childhood, early, and late adolescence. We hypothesized that children residing in areas with more street-view trees would have better CVH from mid-childhood to late adolescence based on the findings of similar studies in the past.[22] Given that CVH may differ by urbanicity,[23] and that children's age, sex, race and ethnicity,[24] as well as neighborhood socioeconomic status (SES),[25] may influence the association of greenspace with CVH, we also examined effect modification by these characteristics.

METHODS

Data

We used data from Project Viva, a pre-birth, US-based cohort Between 1999 and 2002, Project Viva recruited pregnant women from a large group practice in eastern Massachusetts and has followed mother-child pairs since pregnancy, even if they relocated outside of Massachusetts.[26] Initially, we recruited 2,128 liveborn singleton infants, among whom 1,279 participated in mid-childhood (mean age: 8.0±0.8y) in-person visit (2007–2011); 1,177 participated in early adolescent (13.3±1.0y) visits (from 2012–16), and 809 participated in late adolescent (17.8±0.7y) visit (2017–2021). All mothers provided written informed consent at each visit, and children began providing verbal consent at mid-childhood as well as written informed consent when they reached the age of 18 years. The Institutional Review Board of Harvard Pilgrim Health Care approved the study protocols.

Street-view greenspace exposure

We created a street network grid every 100m along the street network for all cities across the US. We identified the nearest Google Street View images from 2007 (the first year of image availability) to 2020 for each grid point. The majority of the GSV images (~78%) were collected from April-October,[27] which suggests that seasonality is unlikely to substantially affect our findings. For each location, we pulled four images (North, South, East, and West) to capture the horizontal vision within the view. We then applied the pyramid scene parsing network (PSPNet) deep learning model,[28] pre-trained on the ADE20K dataset[29] to derive pixel-level segmentation of each image,[30–32] for up to 150 predefined classes of objects (e.g., trees, palm tree, grass) (see Table S1 for a full list).[29] We segmented the following greenspace features to the pixel level: trees, palm trees, grass, plants, fields, and flowers.[29] For each image, the algorithm estimates the percentage of each output class (e.g., 50% trees in an image). We then averaged across the four orientations to estimate the percentages of each class within a 360° view for a given location. For each year, we averaged the percentage of each output class to a 100m resolution raster for every US core-based statistical area (CBSA). If a cell within a CBSA lacked a value in a specific year, we used the closest value in time, if available, which was approximately 45% from the corresponding follow-up year ± 1 year and 72% from the corresponding follow-up year ± 3 years. Details of our methods for deriving street-view greenspace metrics are described in a previous paper.[27]

We linked the 100m street-view greenspace metrics derived by the PSPNet deep learning algorithm to geocoded participant addresses across the US provided at each of three visits (mid-childhood [2007–11], early adolescence [2012–16], and late adolescence [2017–21]) to derive street-view greenspace exposure metrics for the corresponding year (e.g., linking an address from 2007 to street-view data from 2007). We also applied focal statistics-based smoothing (i.e., the average of all 100m grid values within the given radius) to derive street-view exposures at 500m and 1,000m spatial resolutions. The three greenspace exposure metrics included the percentage of trees (trees + palm trees), percentage of grass, and percentage of other green (flowers + plants + fields). We internally standardized all exposure metrics to z-scores, which can be interpreted as an increase or decrease per standard deviation (SD) for each greenspace metric, and allow for direct comparison of effect estimates between different greenspace metrics. We used 500m as the primary exposure radius as recommended in previous studies to represent typical extents of children's residential neighborhoods.[33]

Cardiovascular health outcomes

We assessed children's CVH using the AHA Life's Essential 8 (LE8) score.[34] LE8 consists of four behavioral components (sleep, physical activity, diet, and nicotine exposure) and four biomedical components (blood lipids, blood glucose, body mass index [BMI], and blood pressure), each with a scoring algorithm ranging from 0 to 100-points. Following the AHA guidelines, we calculated the LE8 score for each child at a given time point (e.g., mid-childhood) from the unweighted average of the scores of all eight components.[34] The LE8 score ranges from 0 to 100, with higher scores indicating better CVH. Details of the assessment of the individual components of LE8 are presented in Table S2. To ensure the most accurate measurement of CVH at each time point, we only included children with scores for all eight individual components available.

Covariates

We extracted the sex of the child from the delivery hospital medical records. Teen reported their race and ethnicity at the early childhood visit, and if missing, we filled in the mother-reported child race and ethnicity. We categorized race and ethnicity as non-Hispanic white, non-Hispanic Black, Hispanic, and other races. We viewed race and ethnicity as societal constructs, not deterministic biological causes of disease risk, and included them as proxy measures of structural racism that may impact access to residential greenspace and resources that promote CVH.[35] Mothers self-reported their highest education level and their partner's highest education via questionnaires and interviews during recruitment in early pregnancy, which we categorized as having obtained a college degree (yes/no). Mothers also self-reported their household income (>$70 000/≤$70 000 per year) and marital status (married and/or cohabiting: yes/no) at the mid-childhood visit. Area-level covariates include neighborhood socioeconomic status (SES) using census tract-level median annual household income (continuous; $) and census tract-level population density (continuous; people per mi^2), both linked to residence at mid-childhood visit. We selected these covariates based on previous findings[15] and directed acyclic graphs.[36]

Statistical Analyses

We fitted several regression models to quantify the cross-sectional and longitudinal associations of three street-view greenspace metrics (%trees, %grass, and %other greenspace) with CVH scores. First, we fitted linear regression models to examine the cross-sectional associations of street-view greenspace with children's CVH scores measured at three time points (mid-childhood, early adolescence, and late adolescence). Second, we applied two generalized estimating equation (GEE) models to examine the longitudinal relationships between baseline street-view greenspace (either mid-childhood or early adolescence) and children's CVH scores at baseline and subsequent time points (e.g., mid-childhood exposure outcomes at mid-childhood, early, and late adolescence visits). Additionally, for both models, we included a multiplicative interaction term between each greenspace measure and the child's age at outcome to investigate whether greenspace exposure is associated with CVH score trajectories over time. Lastly, we conducted a linear regression analysis to examine if cumulative, long-term exposure to street-view greenspace from mid-childhood to late adolescence (average estimates) was associated with CVH scores in late adolescence.

For statistically significant associations ($p<0.05$), we further examined whether the associations could be driven by the behavioral or biomedical domains of LE8 scores. We fitted generalized additive models to examine potential nonlinear associations (Figure S1); however, penalized splines did not indicate deviations from linearity (p-value>0.1); thus, we present results from linear models.

In all models, we concurrently included all three street-view greenspace metrics to examine the independent impact of specific greenspace on CVH. Our fully adjusted models included child's age, sex, and race and ethnicity; mother's education level; partner's education level; household income; and neighborhood median household income and population density. We used multiple imputation by chained equations to impute missing covariate data with 20 iterations. This resulted in 20 imputed datasets for all participants in the analytic sample. We then ran regression analyses across 20 imputed datasets and reported the pooled estimates. Imputed results were broadly comparable to those obtained using observed values; the former are presented.

Effect Modification

We examined potential effect modifications by children's sex (male vs. female), race and ethnicity (non-Hispanic white/non-Hispanic Black/Hispanic/other races and ethnicity), neighborhood population density (tertiles of people per mile^2), and neighborhood median household income (in tertiles) for the association between street-view greenspace and CVH scores. We fit models that included a multiplicative interaction term between each greenspace measure and the effect modifier, and used likelihood ratio tests (*P*-interaction <0.05) to determine the statistical significance of the effect modification. For statistically significant interactions, we reported stratum-specific coefficients and 95% confidence intervals (CIs) by the level of each modifier.

Sensitivity analyses

To evaluate whether the results were robust to differently operationalized greenspace measures (i.e., street-view vs. satellite-based) and buffer sizes applied to derive street-view greenspace datasets, we conducted three sensitivity analyses. First, we tested whether our results were sensitive to neighborhood buffer sizes by swapping the 500m exposure radius with the 100m and 1,000m datasets. Second, we included satellite-based greenness measures in the models to examine the associations contributed by street-view metrics independent of satellite-based measures. We derived the satellite-based NDVI at 270 m resolution around the residential address of each participant at three study visits by applying focal statistics-based smoothing (i.e., the average of all 30m grid values of Landsat NDVI estimate range of 0–1 for July of the respective year in which the visit took place). Third, we additionally adjusted mother's pre-pregnancy BMI to account for the impact of parental weight status (a proxy for their CVH) on children's CVH.[37] All statistical analyses were performed in R version 4.3.0 (R Core Team, Vienna, Austria).[38]

RESULTS

Our final analysis sample included 513 children who had both street-view greenspace exposure data and information on all eight CVH metrics at mid-childhood visit, 513 who had both in early adolescent visit, and 451 who had both in late adolescent visit. The consort diagram for analysis sample inclusion is shown in Figure S2. No substantial differences in participant characteristics were observed between between those (N=513) who had all eight individual component scores for LE8 scores to be calculated and those (N=689) who only had some individual components (see Table S3), as well as between those (N=513) who were in the analytical sample and those (N=603) were excluded (see Table S4).Mean LE8 scores were 83.2 (SD=8.0; median=85.0; IQR=10.0) at mid-childhood visit. The mean age of participants at mid-childhood was 7.9 (0.8) years, and 61% of the sample was non-Hispanic White (Table 1). Children with higher exposure to street-view greenspace (sum of %trees, %grass, and %other greenspace) were more likely to be identified as non-Hispanic white, had mothers who were more likely to be married, had higher educational attainment and household income, and resided in neighborhoods with higher neighborhood SES and lower population density (Table 1). Street-view trees were moderately correlated with grass (r=0.55) and very weakly correlated with other green (r=0.07). The correlation between the street-view metrics of greenspace and NDVI varied according to vegetation type (Figure S3). The correlation coefficients differed only slightly in early and late adolescence.

In the unadjusted models, a higher percentage of street-view trees was associated with higher CVH cross-sectionally at all three time points (left panel of Figure 1). There was also some evidence for a positive association of other green with CVH, but there was no evidence for an association of % grass with CVH in any analysis. Most of the observed associations were attenuated to null after adjustment for individual and neighborhood confounders (right panel of Figure 1), with neighborhood SES having the greatest impact on the estimate (see Figure S4). The only exception was the association of street-view trees with CVH in late adolescence; where each SD higher street-view trees within a 500m buffer of residential addresses remained associated with 1.92-points higher LE8 scores (95%CI: 0.50, 3.35) in late adolescence (Figure 1). The last adolescent association was mainly driven by the four biomedical components (2.40, 95%CI: 0.54, 4.26) than by the four behavioral components (0.44, 95%CI: −1.00, 1.88) (see Figure S5). The results were consistent when examining street-view metrics within the 1000m buffer increase per SD increase in %trees) (Figure S6a), although the cross-sectional association in late adolescence attenuated when examining metrics within the 100m buffer (Figure S6b). In the models (Figure S6c) additionally adjusted for satellite-based NDVI, the results for street-view metrics were consistent with our main analyses, and the associations for NDVI were null. The associations for NDVI were also null for the model without street-view metrics (Figure S6d). The results were also consistent when additionally adjusted for mother’s pre-pregnancy BMI (Figure S6e)

Figure 2 presents the results of models examining the longitudinal relationships between street-view greenspace metrics and CVH scores measured at three time points. No associations were found between the three greenspace metrics in mid-childhood and CVH scores at the same and subsequent time points (Model 1, see Figure 2), nor between the metrics in early adolescence and CVH scores in early and late adolescence (Model 3, see Figure 2). Additionally, no associations were identified between any of the greenspace metrics and CVH score trajectories over time (Models 2 and 4, see Figure 2). Finally, cumulative greenspace exposure from mid-childhood to late adolescence showed no association with CVH scores in late adolescence (Model 5, see Figure 2).

We observed some evidence of effect modification by race and ethnicity, and neighborhood SES for cross-sectional associations between %trees and CVH at the mid-childhood and early adolescent visits, but not for sex and population density (see Figure 3). For example, we observed that a higher percentage of street-view trees was associated with somewhat higher LE8 scores among non-Hispanic White participants in early adolescence, but somewhat lower LE8 scores among all other racial and ethnic groups (*P*-interaction=0.01), although in stratified analysis, all associations were not significant (e.g., 0.97-point [95%CI: −0.15, 2.09] per SD increase in %trees among non-Hispanic White adolescents) (Figure 3). We also found that a higher percentage of street-view trees was associated with higher LE8 scores in mid-childhood among children living in neighborhoods in the highest SES tertile [β 2.18-point [95%CI: 0.20, 4.16] per SD increase), whereas associations were null among the lower two tertiles (*P*-interaction=0.04) (Figure 3). We found no evidence of effect modification by individual and neighborhood factors for the cross-sectional associations between any of the three street-view metrics in late adolescence (Figure 3).

DISCUSSION

In this cohort of US children, we found no overall cross-sectional nor longitudinal relationships of three street-view greenspace metrics (i.e., trees, grass, and other greenspace) to CVH scores across mid-childhood, and early and late adolescence. The only exception was the cross-sectional association between street-view trees and CVH in late adolescence, in which a higher percentage of street-view trees within 500m of participants' homes was associated with higher CVH scores in late adolescence. Late-adolescent results were consistent with the choice of using a larger neighborhood buffer size and persisted after adjusting for traditional satellite-based greenspace exposure. Although we did not find overall associations of street-view greenspace metrics with CVH scores at mid-childhood or early adolescence, there was also some evidence of stronger associations between street-view trees and CVH in mid-childhood and early adolescence among non-Hispanic white children or children from the highest neighborhood SES tertiles.

Our overall null findings on the associations between street-view greenspace metrics and CVH in 517 children in eastern Massachusetts add to the very limited literature reporting mixed results on relationships between greenspace exposure and CVH in children and adolescents. Our findings are consistent with a Dutch study of 1505 adolescents that also found no cross-sectional associations between NDVI and a cardiometabolic risk score derived on the basis of metabolic syndrome components (similar to the biomedical components of LE8 scores we used) in a group of participants aged 12 and 16 years,[15] whereas our results are inconsistent with a study of 725 children and adolescents aged 5 to 17 years in Florida, which reported that lower neighborhood NDVI was cross-sectionally associated with higher BMI and higher systolic and diastolic blood pressure in early to late adolescence.[39] This could be due to the NDVI measure used in the two previous studies, which combined all types of greenspace that may or may not be associated with CVH, or that have different directions of association. In contrast, the street-view greenspace metrics used in our study allowed us to distinguish the potential impact of certain types of greenspace, such as trees, on CVH. This was corroborated by our sensitivity analysis results, including satellite-based measures, in which we found that street-view trees, but not NDVI, were associated with CVH.

We found a positive cross-sectional association between street-view trees and CVH in late adolescence but not in mid-childhood or early adolescence. It could be that participants in late adolescence had more autonomy to seek out or use different types of greenspace in residential neighborhoods than in earlier life stages.[40] Interestingly, our exploratory analyses suggest that the positive association was mainly driven by the biomedical components (i.e., BMI, blood glucose, blood lipids, and blood pressure) of CVH. This suggests that the influence of street-view trees on CVH may be through non-behavioral pathways, such as alleviation of psychological distress of greenspace, which have been associated with the incidence and prevalence of CVD in past studies.[41,42] We found no association between street-view grass and other greenspace and CVH scores across three visits. Grass may be an important indicator of the presence of neighborhood parks and open space near residential locations. However, these parks and open space may not be ones that children and adolescents frequent and therefore may have less influence on their CVH.[43]

We found that the association between street-view trees and CVH scores was more pronounced among non-Hispanic white participants in their early adolescence. This may be because other racial and ethnic groups were more influenced by other components of neighborhood greenspace that may not be captured or only partially captured by our street-view metrics,[44,45] such as backyards, home gardens, off-street parks, and playgrounds. Our findings on differed associations by neighborhood SES in mid-childhood are consistent with previous research showing that higher tree canopy is associated with better sleep, more physical activity, and lower odds of childhood overweight and obesity – all of which are LE8 components – in neighborhoods with higher SES.[8,46,47] In contrast, residents of lower SES neighborhoods are less likely to use existing greenspaces, possibly due to their low quality, lack of amenities, and street crime.[48,49]

This study has several limitations. First, the limited sample size could be a reason for the relatively wide CIs, especially in the results of the stratified analyses for racial and ethnic subgroups. Second, street-view imagery itself has limitations as it excludes behavioral aspects of exposure, including greenspace exposure not captured by street-view imagery (e.g., backyard, playground away from streets).[50] Imagery is also a snapshot of a place at a particular point in time and may not provide an accurate representation of seasonal variability. However, we believe that a systematic bias affecting the observed findings is unlikely because most images were taken during warmer seasons and at a time that was completely independent of our outcome data. Further, we also carefully designed our metric to mitigate this influence (e.g., by categorizing flowers with other plants as “other greenspace”). In this study, we used images from within 500m of a participant’s address, and our results were consistent with the sensitivity analyses that used 100m and 1,000m. Nevertheless, the images we used may still not be representative where participants spend all of their time (e.g., school exposure).[51,52] This may contribute to exposure measurement errors and lead to spurious results when examining associations between greenspace and children’s CVH.[40,53] Additionally, both the satellite-based and street-view greenspace metrics used in the studies did not take into account participants’ perceived exposure to greenspace such as aesthetics, design, and functionality (e.g., availability of playgrounds or equipment), which may be relevant to health behaviors and outcomes related to CVH.[54] Finally, we examined several cross-sectional and longitudinal associations between street-view greenspace metrics and CVH, which may lead to potential multiple testing issues when interpreting the statistical findings of this study, particularly in the analyses of effect modification. Furthermore, although we included several measures of SES in our analyses, our results may still be subject to residual confounding by other unmeasured socioeconomic factors.[55] Our focus on examining associations rather than causal relationships further limits causal assertions. However, given the extremely limited studies in the past, we believe that examining relationships at different timepoints is necessary to account for many potential pathways linking greenspace to individual components of LE8 score at different life stages of children.[56] Further, we note that all associations observed were in hypothesized directions.

Despite these limitations, our study has several important strengths. First, it used a novel and validated composite measure of CVH in children. Previous studies have mostly focused on the associations of neighborhood greenspace with individual drivers of CVH, such as physical activity, sleep, BMI, blood pressure, and various CVD outcomes. Our findings thus provide further evidence on the potential role of specific features of greenspace in further promoting individual and population CVH health, an aspect that has not been as emphasized in previous health promotion efforts.[34] Second, this study uses novel, objectively measured street-view greenspace metrics representing ground level compared to previous studies that applied satellite-based data. Our approach benefits from advances in computer vision and deep learning, resulting in more accurate exposure metrics corresponding to ground-level perspectives. This allowed us to examine the role of specific features of greenspace, such as trees and grass, in association with CVH, and isolate the potential beneficial effects of trees in particular. Third, compared to most studies that have examined the cross-sectional relationships between neighborhood greenspace and children's health behaviors and CVH-related outcomes at one point in time, our research also assessed changes in CVH over time relative to baseline greenspace exposure, as well as cumulative greenspace exposure from mid-childhood to late adolescence in relation to late adolescent CVH, offering deeper insights into the long-term impact of greenspace on CVH during various growth stages in children.

CONCLUSION

To the best of our knowledge, this study is the first to integrate deep learning methods into greenspace exposure assessment and explore its associations with a composite measure of CVH in children and adolescents. Overall, our study found no cross-sectional nor longitudinal association between street-view greenspace and CVH in Project Viva children, except for the cross-sectional protective association between street-view trees and CVH in late adolescence. There was also some evidence of stronger associations between street-view trees and CVH in mid-childhood and early adolescence among non-Hispanic white children or children from the highest neighborhood SES tertiles. To date, only a handful of studies have examined greenspace and CVH in children. Thus, more research is needed in this area, as CVH during childhood has been associated with many chronic diseases in adulthood.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Highlights

- We examined associations of greenspace associations with cardiovascular health (CVH) throughout childhood and adolescence
- Participants in the Project Viva cohort had their CVH scores assessed by Life’s Essential 8 algorithm
- Greenspace exposure, including trees, grass, flowers, and plants, were derived from street-view images
- Street-view greenspace was not associated with CVH longitudinally
- Cross-sectionally, street-view trees were protectively associated with CVH at late adolescence

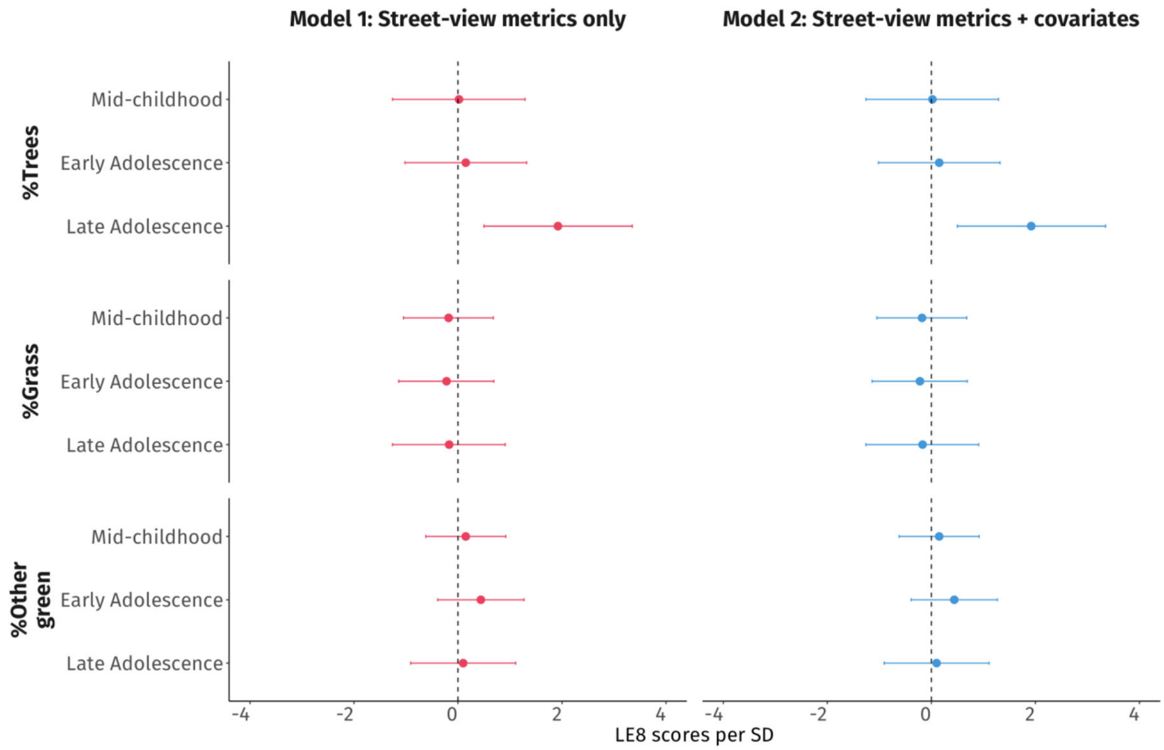

Figure 1.

Estimates of cross-sectional associations between three street-view greenspace metrics and cardiovascular health scores (LE8) in children from Project Viva

Model 1: %trees, %grass, and %other greenspace mutually adjusted.

Model 2: Fully Adjusted. Model 1 + age, sex, race and ethnicity, maternal education, paternal education, marital status, household income, neighborhood median income, and population density.

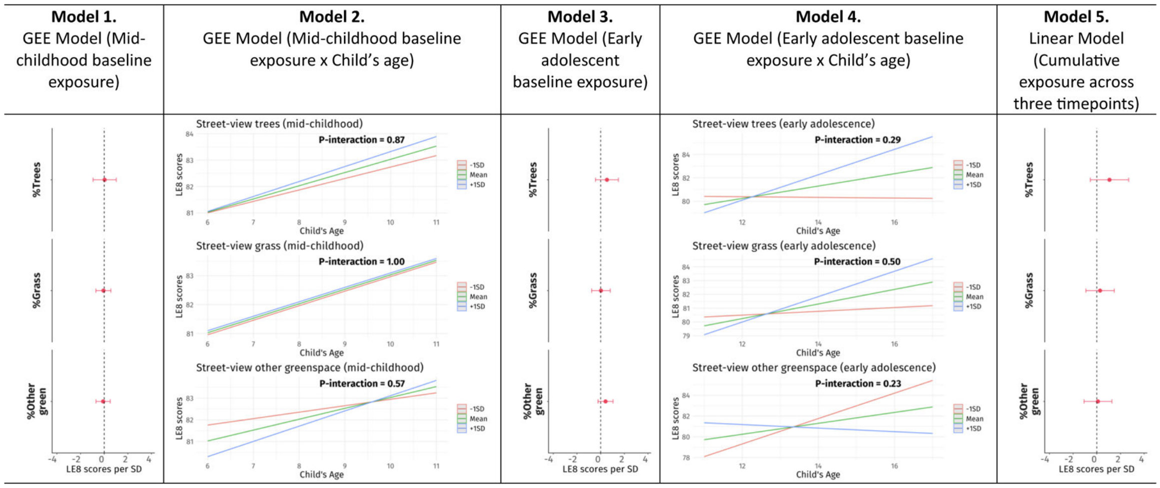

Figure 2.

Estimates of longitudinal associations between three street-view greenspace metrics and cardiovascular health scores (LE8) in children from Project Viva

GEE = generalized estimating equation.

In all models, %trees, %grass, and %other greenspace variables were mutually adjusted. Additional covariates included age, sex, race and ethnicity, maternal education, paternal education, marital status, household income, neighborhood median income and population density, except for the stratifying variables.

In model 5, cumulative greenspace exposure metrics was calculated by averaging the exposure estimates of each metric (%trees, %grass, %other greenspace) across three timepoints (mid-childhood, and early and late adolescent visits).

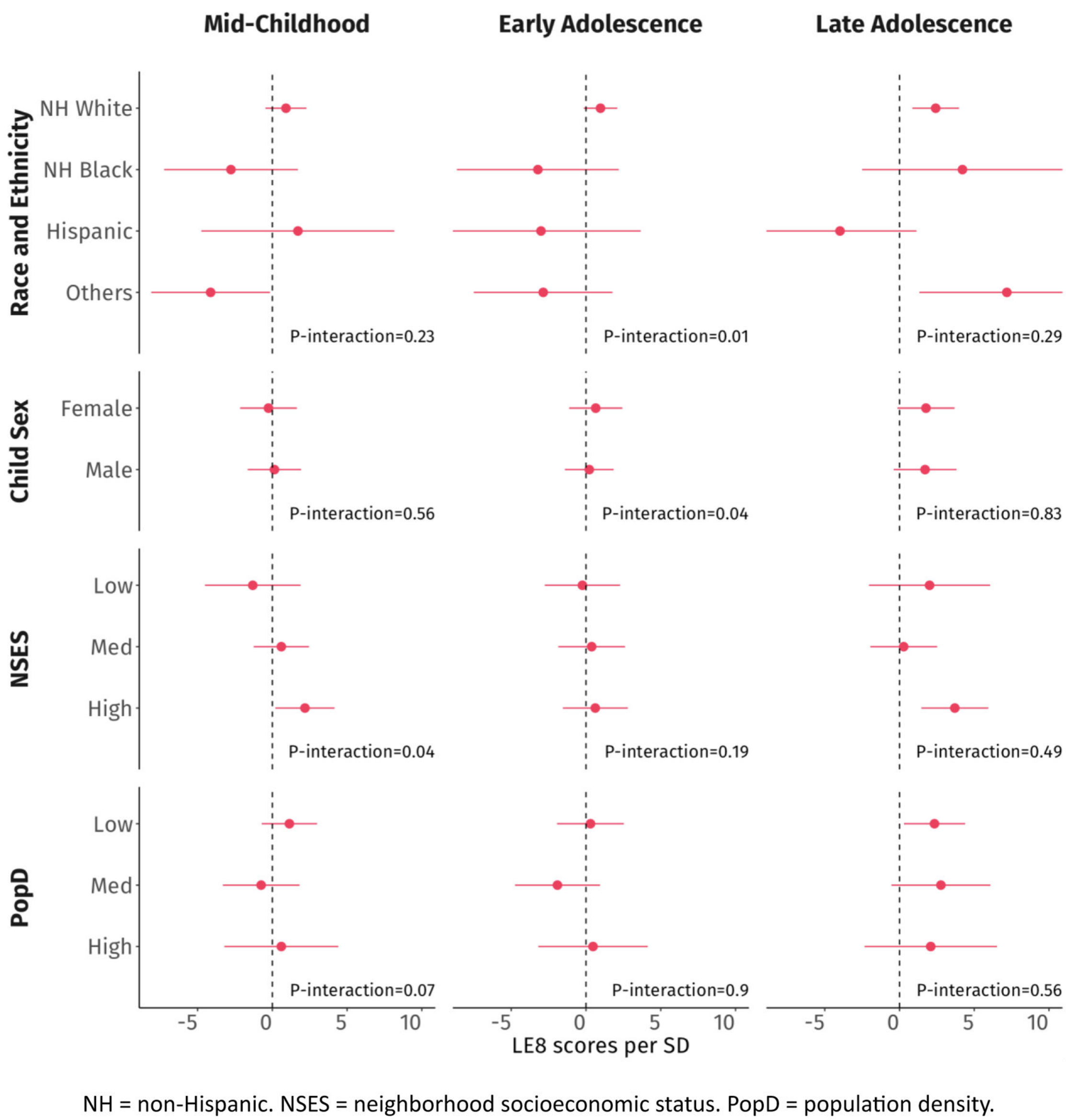

Figure 3.

Effect modification by race and ethnicity, child sex, neighborhood socioeconomic status (NSES), and population density of the cross-sectional associations between street-view trees and cardiovascular health (LE8 scores) in mid-childhood, early adolescence, and late adolescence in Project Viva children %trees, %grass, and %other greenspace were mutually adjusted. Additional covariates included age, sex, race and ethnicity, maternal education, paternal education, marital status, household income, neighborhood median income and population density, except for the stratifying variables.

LE8 = Life's Essential 8.

Table 1.

Baseline characteristics (mid-childhood visit) of study participants in Project Viva by quartiles of street view imagery-based greenspace (trees + grass + other greenspace)

Variable	Overall N = 513	Quartile 1 N = 136	Quartile 2 N = 128	Quartile 3 N = 129	Quartile 4 N = 120
Child's age, (mean±SD)	7.9 ± 0.8	7.9 ± 0.8	7.9 ± 0.8	7.9 ± 0.7	7.7 ± 0.7
Child's race and ethnicity, n (%)					
Non-Hispanic white	313 (61.1%)	41 (30.4%)	81 (63.3%)	88 (68.2%)	103 (85.8%)
Hispanic	49 (9.6%)	25 (18.5%)	13 (10.2%)	7 (5.4%)	4 (3.3%)
Non-Hispanic Black	99 (19.3%)	59 (43.7%)	18 (14.1%)	17 (13.2%)	5 (4.2%)
Other race and ethnicity	51 (10.0%)	10 (7.4%)	16 (12.5%)	17 (13.2%)	8 (6.7%)
Missing/Not provided	1 (0.2%)	1 (0.7%)	0 (0.0%)	0 (0.0%)	0 (0.0%)
Child's sex % female, n (%)	253 (49.3%)	66 (48.5%)	69 (53.9%)	56 (43.4%)	62 (51.7%)
Mother's education % college, n (%)	337 (66.1%)	57 (42.9%)	89 (69.5%)	91 (70.5%)	100 (83.3%)
Missing/Not provided	1 (0.2%)	1 (0.7%)	0 (0.0%)	0 (0.0%)	0 (0.0%)
Father's education % college, n (%)	302 (65.9%)	45 (42.1%)	68 (60.2%)	93 (76.2%)	96 (82.8%)
Missing/Not provided	55 (10.7%)	29 (21.3%)	15 (11.7%)	7 (5.4%)	4 (3.3%)
Mother's marital status % married, n (%)	439 (86.6%)	105 (78.4%)	105 (82.7%)	117 (90.7%)	112 (95.7%)
Missing/Not provided	6 (1.2%)	2 (1.5%)	1 (0.8%)	0 (0.0%)	3 (2.5%)
Household income % greater than $70K, n (%)	349 (69.7%)	56 (43.1%)	87 (69.6%)	104 (82.5%)	102 (85.0%)
Census tract median household income (1,000$), (mean±SD)	63.6 ± 23.3	41.7 ± 13.7	61.0 ± 17.3	70.5 ± 16.3	83.4 ± 22.7
Missing/Not provided	5 (1.0%)	2 (1.5%)	2 (1.6%)	1 (0.8%)	0 (0.0%)
Census tract population density (people per mi^2), (mean±SD)	688.8 ± 331.3	1,019.5 ± 99.2	812.1 ± 181.6	582.4 ± 237.3	283.9 ± 218.3
Missing/Not provided	33 (6.4%)	6 (4.4%)	10 (7.8%)	7 (5.4%)	10 (8.3%)
Life's Essential 8 scores, (mean±SD)	83.2 ± 8.0	81.6 ± 9.4	82.4 ± 8.0	83.2 ± 7.5	86.0 ± 6.0
Street-view greenspace metrics, (mean±SD)					
% Trees	27.7 ± 10.1	15.7 ± 3.3	24.6 ± 3.2	30.6 ± 3.2	41.3 ± 6.2
% Grass	5.1 ± 3.5	1.7 ± 1.3	4.4 ± 2.5	6.9 ± 2.9	7.8 ± 3.2
% Other greenspace (Plants + Fields + Flowers)	1.8 ± 0.8	1.6 ± 0.6	1.9 ± 0.7	1.8 ± 0.8	1.9 ± 0.8
Satellite-based NDVI (0~1), (mean±SD)	0.6 ± 0.1	0.4 ± 0.1	0.6 ± 0.1	0.7 ± 0.1	0.7 ± 0.1

NDVI = normalized difference vegetation index.