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Differential associations of the built environment on weight gain by sex and race/ethnicity but not age

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Abstract

Objective: To explore the built environment (BE) and weight change relationship by age, sex, and racial/ethnic subgroups in adults.

Methods: Weight trajectories were estimated using electronic health records for 115,260 insured Kaiser Permanente Washington members age 18–64 years. Member home addresses were geocoded using ArcGIS. Population, residential, and road intersection densities and counts of area supermarkets and fast food restaurants were measured with SmartMaps (800 and 5,000-meter buffers) and categorized into tertiles. Linear mixed-effect models tested whether associations

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Author contributions: JFB, AD, and DA developed the initial study concepts. AVM and PMH developed the SmartMaps exposure assessment tool. JFB, AC, MC, SJM, DA, and JHB developed the study design and analytic plan with consultation from all other co-authors, and JFB conducted analyses. JHB wrote the manuscript with the assistance of AD and under the supervision of AD and DA. All authors provided critical feedback and helped shape the research, analysis, interpretation of findings, and the manuscript. AD and DA provided project supervision. JA provided project support.

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between BE features and weight gain at 1, 3, and 5 years differed by age, sex, and race/ethnicity, adjusting for demographics, baseline weight and residential property values.

Results: Denser urban form and greater availability of supermarkets and fast food restaurants were associated with differential weight change across sex and race/ethnicity. At 5 years, the mean difference in weight change comparing the 3rd versus 1st tertile of residential density was significantly different between males (−0.49 kg, 95% CI: −0.68, −0.30) and females (−0.17 kg, 95% CI: −0.33, −0.01) (P-value for interaction = 0.011). Across race/ethnicity, the mean difference in weight change at 5 years for residential density was significantly different among non-Hispanic (NH) Whites (−0.47 kg, 95% CI: −0.61, −0.32), NH Blacks (−0.86 kg, 95% CI: −1.37, −0.36), Hispanics (0.10 kg, 95% CI: −0.46, 0.65), and NH Asians (0.44 kg, 95% CI: 0.10, 0.78) (P-value for interaction < 0.001). These findings were consistent for other BE measures.

Conclusion: The relationship between the built environment and weight change differs across demographic groups. Careful consideration of demographic differences in associations of BE and weight trajectories is warranted for investigating etiological mechanisms and guiding intervention development.

Keywords

geographic information systems; electronic medical records; obesity; residential density; disparities

INTRODUCTION

Neighborhood built environment (BE), alongside underlying area social and economic conditions, is thought to influence body weight through energy balance behaviors – physical activity (PA) and diet [1–3]. Urban form features of the BE that encourage recreational activities and walking (e.g., parks and residential density) have been linked to higher PA and lower body weight [3–8]. The link between neighborhood food environment, diet, and body weight, has been less consistent [3,9]. One study found that the colocation of PA-promoting BE features and healthy food sources were more negatively associated with body weight than any single BE feature [10]. Previous analysis of the Kaiser-Permanente Washington (KPW) Moving to Health (M2H) cohort showed that denser urban form and greater availability of both supermarkets and fast food restaurants were associated with somewhat lower weight gain (<0.5 kg) [11]. Jointly accounting for urban form and the food environment nullified the apparent inverse association between the latter and body weight [11]. However, this modest average association between the BE and weight trajectories may be masking more pronounced associations among select demographic subgroups.

The neighborhood BE might be differentially associated with changes in body weight across three individual-level demographic factors – age, sex, and race/ethnicity. Age may influence the types, duration, and level of BE exposures [4,12]. Level of exposure and susceptibility to certain aspects of the BE might affect males and females differently [8,12–14]. The BE's relationship with weight trajectories may also not be comparable across racial/ethnic groups due to differences in neighborhood resources stemming from a history of structural racism, residential segregation, and persistent differences in neighborhood inequities [15–18].

Although prior studies have evaluated the relationship between the BE and obesity in the general population and for specific age, sex, or racial/ethnic groups, few have examined whether these factors might modify the BE-obesity relationship [19]. Fewer still have examined their influence on long-term weight trajectories. Assessing the heterogeneity of the BE's association with weight trajectories can aid our understanding of the precise link between place and health and guide future interventions. The present study sought to determine whether the BE was differentially associated with weight trajectories across age, sex, and racial/ethnic strata.

METHODS

Study population and design

The M2H retrospective cohort has been previously described [11,20,21]. Information on residential history, measured heights and weights, and health was extracted from KPW member electronic health records (EHR) receiving care from 1/1/2005 to 4/30/2017. Members were included if they were active within the KPW system, were age 18–64 years at baseline, and had 270 days of continuous enrollment during this period. Members' insurance status was verified at enrollment and gaps in enrollment of 92 days were permitted. Members who had a prior-year cancer diagnosis (omitting non-melanoma skin cancer), had prior-year bariatric surgery, were pregnant or within 3 months after delivery, of unknown sex, had a non-geocodeable address, had an address geocoded to a location outside of King County, or had an unknown residential property value at baseline were excluded from the cohort (Figure 1).

Measuring height and body weight

Height, in m, and body weight, in kg, were measured by trained clinicians and recorded in the EHR at each visit. Body weights (<31.75 kg or >317.52 kg) and heights (<1.22 m or >2.44 m) that clinicians flagged as biologically implausible (<31.75 or >317.52 kg) were excluded [20]. Body mass index (BMI) was calculated by dividing each member's weight in kilograms by their height in meters squared. Obesity was defined as a BMI at or exceeding 30 kg/m^2. BMI values <15 kg/m^2 or >100 kg/m^2 were considered biologically implausible. The analytic sample was limited to members with at least one follow-up weight measure. Members were tracked for successive weight measures from the point at which their first baseline weight was taken until the end of the observation period and were censored due to: a residential move, having a subsequent address that could not be geocoded, bariatric surgery, cancer diagnosis, KPW disenrollment, or gap in address data of ≥13 months. Members were also censored when they turned 65 years old. We also excluded follow-up weights that were taken 9 months prior to a pregnancy outcome and 3 months after the end of a pregnancy [20].

Built environment exposure assessment

Member addresses were geocoded using ArcGIS Desktop and King County (KC), WA address point reference data. Additional geocoding protocol details for M2H have been described previously [11,20,21]. Latitude and longitude point data from geocoded addresses in KC were linked to SmartMaps measuring BE features described below to determine neighborhood exposures [22]. Members' baseline BE exposures were matched temporally to their year of entry into the cohort. Yearly data were available for residential density and property values. For all other BE exposures, members were matched to nearest year for which data were available (Supplemental Table 1) [11,20,21]. SmartMaps are continuous rasterized surfaces that provide estimates of BE measures within a given area [22–25]. Additional information on SmartMap development and procedures has been published elsewhere [20–22].

Primary urban form measures of the BE were residential density, population density, and street intersection density measured at baseline. Residential and population density were selected as they have been shown to be highly predictive of walkability and prevalent obesity [4,11,12,26–30]. Both measures were also highly correlated in our cohort (r=0.92). Street intersection density has been used in prior work as a measure of walking route connectivity and shown to be associated with prevalent obesity [31]. These density measures represented SmartMap-based counts of BE features per hectare within 800 m Euclidian-based buffers (10-minute walk) from the baseline address [22]. BE exposures were modeled using tertiles (rather than a continuous parameterization) to enable ease of interpretation given our longitudinal analysis approach, which flexibly modeled weight trajectories over time across levels of exposure. Sensitivity analyses in our prior work revealed that associations between the BE and weight change were not sensitive to the choice of cut-points [11].

To characterize the food environment, we used counts of supermarkets and fast food restaurants, which encompassed all quick service restaurants where one pays for food first before eating [32]. We used network-based SmartMaps to sum food establishments within a 5,000 m buffer (equivalent to a short drive) from the baseline address. Fast food restaurant and supermarket counts were also categorized into tertiles.

Demographic subgroups

We selected age, sex, and race/ethnicity as the demographic factors to evaluate for effect measure modification as few studies have directly compared longitudinal associations between these groups [19]. We restricted age at baseline in our cohort to 18–64 years because weight gain begins to taper off at older ages along with a loss of lean body mass [33]. We dichotomized age into 18–44 and 44–64 years as prior work showed substantially less weight change among 44- to 64-year-olds relative to 18- to 44-year-olds [20,21]. Sex was defined as male and female and was self-reported. The term "sex" reflects the terminology used in the EHR during this study period (2005–2017). Although data collection around sex and gender identity has since improved, in this study we are unable to disentangle the biological differences, owing to sex assigned at birth, from the social pathway attributable to current societal norms around gender identity. Race/ethnicity was defined as non-Hispanic (NH) White, NH Black, NH Asian, and Hispanic based on Census Bureau definitions and the availability of self-identifying racial and ethnic categories in the EHR. Other racial/ethnic groups, including Hawai'ian/Pacific Islander, Native American/Alaskan Native as well as multiracial, and other racial/ethnic identities were included as a covariate in age and sex stratified analyses but were excluded from the analysis of effect measure modification due to sample size limitations. These designations of self-reported race and ethnicity represent member-reported identities in this period and care setting. Through a social/cultural and health equity lens, we anticipate these designations are our best available proxy for the members' exposure to racism and its influence on the BE-weight relationship.

Covariates

We adjusted our model for factors known to be associated with the BE and weight change. Beyond inclusion of baseline age, sex, and race/ethnicity as main effects in the models, we adjusted for having Medicaid (yes, no), baseline weight (nonlinearly via spline terms with 5 degrees of freedom (DF), where the association of baseline weight was allowed to differ by sex), and residential property values (inflation-adjusted, year-specific deciles). Due to the adjustment for baseline weights, we estimate the association between baseline BE exposure and weight change, beyond any observed relationship between baseline BE exposures, or exposures prior to the study period, and baseline weight. The main effect term of baseline age was included in the model nonlinearly via natural cubic spline terms with 10 DF and knots at quantiles. Residential property value was our primary proxy measure for socioeconomic status (SES) since the EHR does not capture metrics typically used to evaluate SES (e.g., income and education). Prior health and social science research have demonstrated that residential property values are highly correlated with individual and area-level SES and are predictive of health [3,34]. Residential property values were measured at the tax-parcel level, and reflect the combined relative, local value of a given home and the land it on which it rests [35]. Medicaid adjustment served as an additional proxy indicator for SES.

Statistical analysis

The present analysis sought to identify differential associations between baseline BE characteristics and 5-year weight change by age, sex, and racial/ethnic strata independent of SES and other demographic characteristics. We used frequencies, means, and standard deviations to describe our study sample and to examine differences in mean body mass index (BMI), prevalent obesity, and BE exposures across demographic and SES factors at baseline. Linear mixed-effect models estimated the association between baseline BE characteristics and weight trajectories within each demographic stratum. Our primary models were defined as:

$$Y_{it}^{g} = \sum_{g=1}^{G} \sum_{k=1}^{K} BE_{ik} \cdot f_k^g(t) + \gamma Z_i + \mathrm{U_i} + \epsilon_{it}$$

where Y_{it}^{g} is the observed weight change of person i of subgroup g from baseline to time t (follow-up weight minus baseline weight), Z is a vector of baseline covariates described below, U_i is the person-specific random intercept, assumed to have an exponential covariance, due to the irregular temporal spacing of follow-up time, and ϵ_{it} is the residual error term. BE is each built environment variable at baseline. The functions $f_k^g(t)$ denote longitudinal changes in weight at the kth level of the categorical BE variable for the *g*th demographic subgroup. Weight trajectories were flexibly modeled using natural cubic splines with 5 degrees of freedom (DF) and knots at quantiles. We then estimated the association between BE and weight change, defined as the mean difference in weight change, comparing the 3rd versus 1st tertile of the BE measure, at 1, 3, and 5 years, for each demographic subgroup. We further tested whether the association between BE and weight change at each time point differed across subgroups (i.e., effect modification) by conducting an omnibus Wald test. We secondarily compared the 2nd versus 1st tertile for each time point and demographic strata. The study was approved by the KPW institutional review board.

RESULTS

Table 1 summarizes baseline sample characteristics, including mean BMI and obesity prevalence. The sample was majority female (60.2%), between the ages of 18–44 (53.3%), and NH White (67.2%). Few were on Medicaid (3.6%). Mean BMI and obesity prevalence were higher for 45–64-year-olds (mean = 28.8, 34.1%) than 18–44-year-olds (mean = 26.9, 23.9%). Mean BMI and obesity prevalence were slightly higher for males (mean = 28.2, 29.8%) than females (mean = 27.6, 28.0%). Mean BMI and obesity prevalence were highest for NH Blacks (mean = 30.3, 43.5%) and were lowest for NH Asians (mean = 25.2, 13.3%). Prevalent obesity was somewhat lower among Medicaid recipients (26.0%) compared to non-recipients (28.8%); however, mean BMI was comparable. Mean BMI and obesity prevalence was higher at lower deciles of residential property values.

There were few notable differences in the distribution of baseline BE exposures by age, sex, and race/ethnicity; however, 18–44-year-olds tended to live in neighborhoods that were more densely populated and had greater fast food and supermarket availability than 44–64-year-olds (Supplemental Table 2). NH Blacks, NH Asians, and Hispanics were more likely to be in moderately dense areas (tertile 2) and areas with a moderate availability of fast food and supermarkets than NH Whites.

Figure 2 displays weight trajectories by age, sex, and race/ethnicity. On average, members tended to gain weight at 1, 3, and 5 years across demographic strata. However, weight gain was substantially more pronounced among 18–44-year-olds with mean weight gain of 0.41 kg (95% confidence interval (CI): 0.36, 0.46), 1.43 kg (95% CI: 1.36, 1.50), and 2.11 kg (2.03, 2.18) at 1, 3, and 5 years, respectively. Weight gain for 44–64-year-olds was negligible. Weight gain was similar for males and females at 1 and 3 years but diverged at 5 years with females gaining more weight than males, 1.01 kg (95% CI: 0.95, 1.08) and 0.86 kg (95% CI: 0.78, 0.93), respectively. NH Blacks and Hispanics experienced a similar rate of weight gain over time which was higher than that NH Whites or NH Asians. At 5 years, NH Blacks and Hispanics gained 1.28 kg (95% CI: 1.09, 1.46) and 1.25 kg (95% CI: 1.04, 1.46), compared to 0.92 kg (95% CI: 0.86, 0.98) and 0.72 kg (95% CI: 0.60, 0.84) for NH Whites and NH Asians, on average, respectively.

Table 2 provides the difference in mean weight change at 1, 3, and 5 years from baseline comparing the highest and lowest categories of baseline BE measures (3rd versus 1st tertile), adjusting for baseline sociodemographic factors and body weight by age group. There was no evidence that the association between the BE and body weight trajectories differed by age. For example, at 5 years, the difference in mean weight change comparing the 3rd versus 1st tertile for population density at 800 m was −0.44 kg (95% CI: −0.60, −0.27) for 45- to 64-year-olds and was −0.33 kg (95% CI: −0.52, −0.15) for 18- to 44-year-olds (P-value for interaction = 0.409). There was similarly no significant difference for residential density (P-value for interaction = 0.438), road intersection density (P-value for interaction = 0.964), fast food count (P-value for interaction = 0.534), or supermarket count (P-value for interaction = 0.166). Comparing the 2nd and 1st tertile of BE metrics yielded similar findings (Supplemental Table 3).

Table 3 provides the difference in mean weight change at 1, 3, and 5 years from baseline comparing the highest and lowest categories of the BE measures by sex after adjustment. There was evidence that the association between urban form and weight change was more pronounced in males than in females. At 5 years, the difference in mean weight change comparing the 3rd versus 1st tertile for population density at 800 m was −0.60 kg (95% CI: −0.79, −0.41) for males and was −0.17 kg (95% CI: −0.34, −0.01) for females (P-value for interaction < 0.001). This 5-year difference was similarly greater in males than in females for residential density (−0.49 kg, 95% CI: −0.68, −0.30 vs. −0.17 kg 95% CI: −0.33, −0.01, P-value for interaction = 0.011) and road intersection density (−0.40 kg, 95% CI: −0.59, −0.21 vs. −0.09 kg 95% CI: −0.25, 0.07, P-value for interaction = 0.010). There was also evidence that the association between the food environment and weight change was greater in males. At 5 years, the difference comparing the 3rd versus 1st tertile of fast food counts was −0.56 kg (95% CI: −0.74, −0.37) for males and was −0.18 kg (95% CI: −0.34, −0.01) for females (P-value for interaction = 0.002). For supermarket counts, this 5-year difference was −0.54 kg (95% CI: −0.73, −0.35) for males and was −0.27 kg (95% CI: −0.43, −0.11) for females (P-value for interaction = 0.031). Results were similar when comparing the 2nd and 1st tertile of BE metrics (Supplemental Table 4).

Table 4 provides the difference in mean weight change at 1, 3, and 5 years from baseline comparing the highest and lowest categories of the BE measures across racial/ethnic strata after adjustment. There was evidence that the association between urban form and weight change differed across racial/ethnic strata. The 5-year difference in mean weight change comparing the 3rd versus 1st tertile of population density was −0.52 kg (95% CI: −0.66, −0.37) for NH Whites, −0.73 kg (95% CI: −1.24, −0.23) for NH Blacks, 0.39 kg (−0.15, 0.93) for Hispanics, and 0.23 kg (95% CI: −0.10, 0.56) for NH Asians (P-value for interaction < 0.001). A similar association was observed for residential density and road intersection density with a difference at 5-years of −0.47 kg (95% CI: −0.61, −0.32) and −0.34 kg (95% CI: −0.49, −0.19) for NH Whites, −0.86 kg (95% CI: −1.37, −0.36) and −1.01 kg (95% CI: −1.48, −0.55) for NH Blacks, 0.10 kg (95% CI: −0.46, 0.65) and 0.32 kg (95% CI: −0.21, 0.86) for Hispanics, and 0.44 kg (95% CI: 0.10, 0.78) and 0.25 kg (95% CI: −0.06, 0.57) for NH Asians, respectively (P-value for interaction <0.001). The 5-year difference comparing the 3rd versus 1st tertile of fast food restaurant count was −0.46 kg (95% CI: −0.61, −0.32) for NH Whites, −0.54 kg (95% CI: −1.03, −0.05) for NH Blacks, 0.19 kg (95% CI: −0.37, 0.75) for Hispanics, and 0.05 kg (95% CI: −0.27, 0.37) for NH Asians (P-value for interaction = 0.005). For supermarket count, the 5-year difference comparing the 3rd versus 1st tertile was −0.53 kg (95% CI: −0.67, −0.38) for NH Whites, −0.67 kg (95% CI: −1.16, −0.18) for NH Blacks, 0.35 kg (95% CI: −0.20, 0.89) for Hispanics, and 0.16 kg (95% CI: −0.16, 0.48) for NH Asians (P-value for interaction <0.001). Results were largely consistent when comparing the 2nd and 1st tertile of BE metrics across racial/ethnic strata; however, there appeared to be no evidence of a significant association for fast food restaurant count at 5 years (P-value for interaction = 0.094) (Supplemental Table 5).

DISCUSSION

The present study found evidence that the association between the BE and weight gain varied by sex and race/ethnicity but not age in a large cohort of insured adults residing in King County, WA. Across all age, sex, and racial/ethnic strata weight gain occurred; however, denser urban forms and greater availability of supermarkets and fast food restaurants was associated with less weight gain at 5 years. This inverse association was more prominent among males than females and among NH Whites and NH Blacks than other racial/ethnic identities. Our prior work has shown that the counterintuitive finding between fast food availability and weight change could be accounted for by residential density in joint analyses [11].

Although studies have evaluated the BE-body weight relationship in specific age groups, few that have directly examined differences across age strata [19]. One study found that greater residential density was more negatively associated with adiposity in 38–50-year-olds than in those older than 50 [12]. Another found that the odds of obesity associated with a 1-year increase in age was 1% higher in areas in the highest quartile of fast food availability compared to the lowest [2]. Another found that greater access to PA facilities and parks was negatively associated with obesity onset in young adulthood but not older ages [36]. Alternatively, we found no difference between 18–44- and 44–64-year-olds. Taken together, the role that age plays in BE-weight change relationship remains an open question [19].

Our finding that the association between BE and weight change was more pronounced in males stands apart from prior work that suggests the BE-obesity association is greater in females [12,17,37]. It has been suggested that this relationship could vary by sex due to differences in the perception of, level of exposure to, and susceptibility to certain aspects of the BE [13]. A review of the relationship between the BE and PA across sex/gender found that denser urban forms were positively associated with greater PA in men and women [37] but the specific BE characteristics that predicted PA differed. In women, access to public transport, dedicated bicycle lanes, and housing density were most predictive. In men, road and intersection density were most predictive [37]. Our results showed that BE-body weight association was consistently stronger for males across all urban form metrics examined: population, residential, and intersection density.

We also found that denser urban forms and greater availability of supermarkets and fast food were associated with differential weight change by race/ethnicity. The associations indicated that the BE may be more protective against weight gain in NH Whites and NH Blacks; however, no association was found in Hispanic and NH Asian individuals. These findings warrant deeper investigation. Broadly, NH Whites are known to benefit more from their social and built environments than minoritized populations, likely due an array of environmental, societal, and psychosocial factors driven by systemic racism [15–17]. One study found that greater availability of supermarkets and fast food restaurants was associated with lower and higher BMI, respectively, in NH Whites only [15]. Another study found that population density and street connectivity did not explain observed race/ethnicity disparities in obesity [17]. Future work should investigate mechanisms explaining this association relevant to racial/ethnic health equity.

This study had several strengths. First, to the authors' knowledge this study represents the first EHR-based evaluation of age, sex, and racial/ethnic differences in the BE-weight trajectory relationship. Second, the large sample size allowed for the evaluation of effect modification across 4 racial/ethnic groups. Third, the high degree of follow-up within this cohort allowed for the evaluation of 5-year weight change. Fourth, using SmartMaps, we were able to assign detailed BE measures to members.

This study also had limitations. First, our BE measures cannot consider variations in exposure duration since pre-study residence duration at the baseline address is unknown. We did not explore the impact of secular changes in the BE on member weight history; however, this will be explored in future analyses. Second, residing in a neighborhood does not predict full use of area resources [38]. The use of large scale geocoded EHR data precluded our ability to establish individualized activity spaces [39,40]. Third, study generalizability may be limited. The M2H cohort was comprised of insured members that are most often employed and therefore excluded many with long-term disability and the uninsured. Also, our evaluation of obesogenic characteristics is primarily focused on a US metropolitan context. Moreover, societal norms and cultural history around sex, race, and ethnicity may also differ across countries. Fourth, this study focuses only on adult weight trajectories; it is unclear if similar associations are present in youth. Fifth, residential property values, a key covariate in this analysis, may not be readily accessible, useful in areas bereft of open markets or with infrequent home sales or rent renewals, or predictive of health in all locations. Sixth, our sex and race/ethnicity definitions were limited to the constraints of the KPW EHR which were collected 2005–2017 before more current and inclusive, self-reported options were available. We therefore were unable to differentiate between sex and gender identities and lacked the power to examine associations in Hawai'ian/Pacific Islander, Native American/Alaskan Native, and other race/ethic identities as well as those identifying with multiple races. Seventh, we did not account for within household or within neighborhood correlation. Our EHR data does not easily enable identification of member households and, while spatial models were considered, additional bias can be introduced by such models when the exposure is spatially varying [41–44]. Development of techniques to account for spatial correlation without the introduction of these biases are an active area of research [44–47].

In conclusion, this analysis found evidence of heterogeneity in the relationship between the BE and weight trajectories across sex and race/ethnicity strata in a large EHR-based cohort of insured adults living in King County, WA. We believe this study highlights the importance of investigating the potential for differential associations across these key demographic characteristics which have, to date, not been well-studied [19]. To do so will require careful consideration and a deeper understanding of the larger social, structural, political, and cultural history underpinning the observed differences in the BE-body weight relationship.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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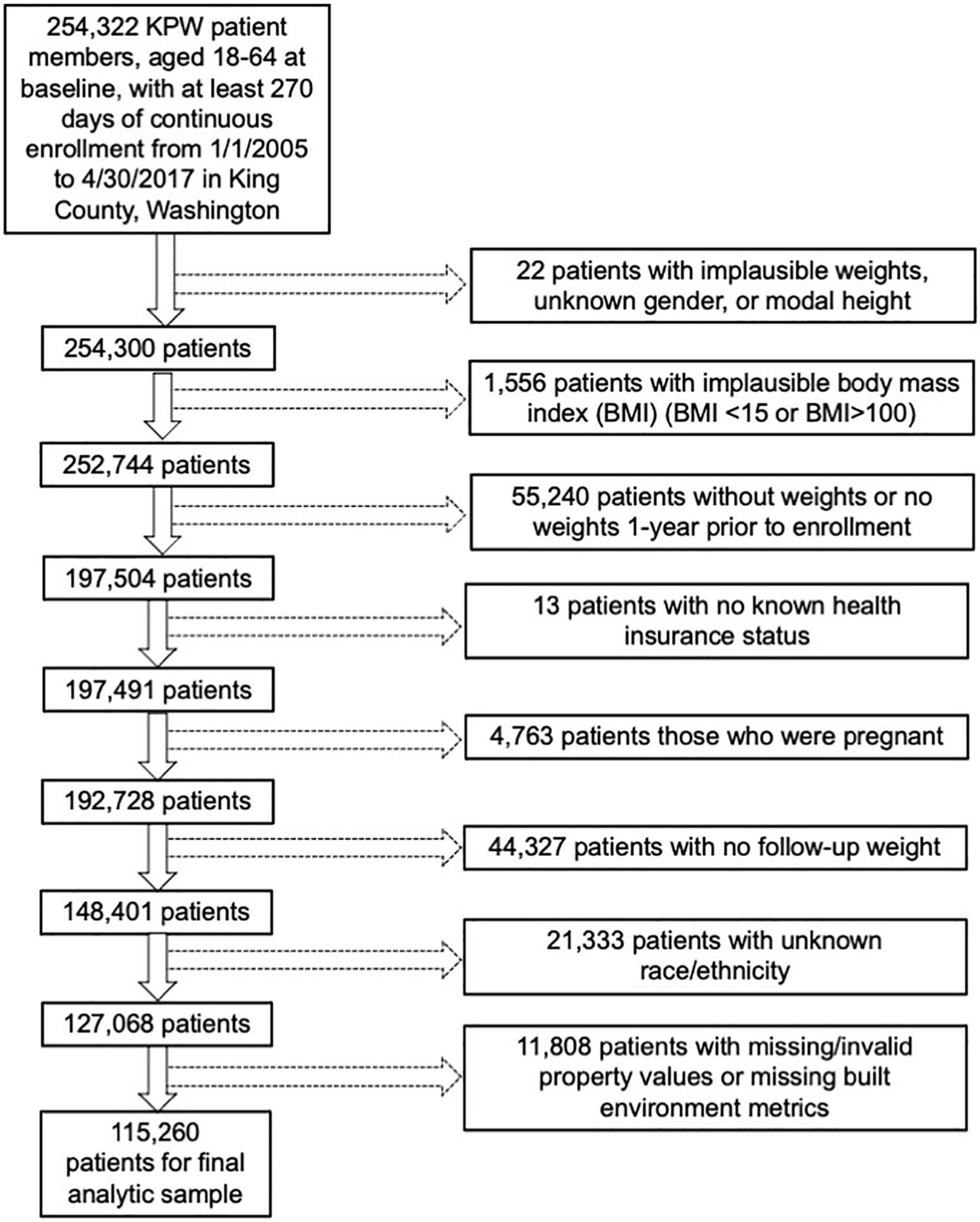

Figure 1.

Analytic sample exclusion/inclusion decision flow diagram

Note: Solid lines indicate inclusions. Dashed lines indicate exclusions.

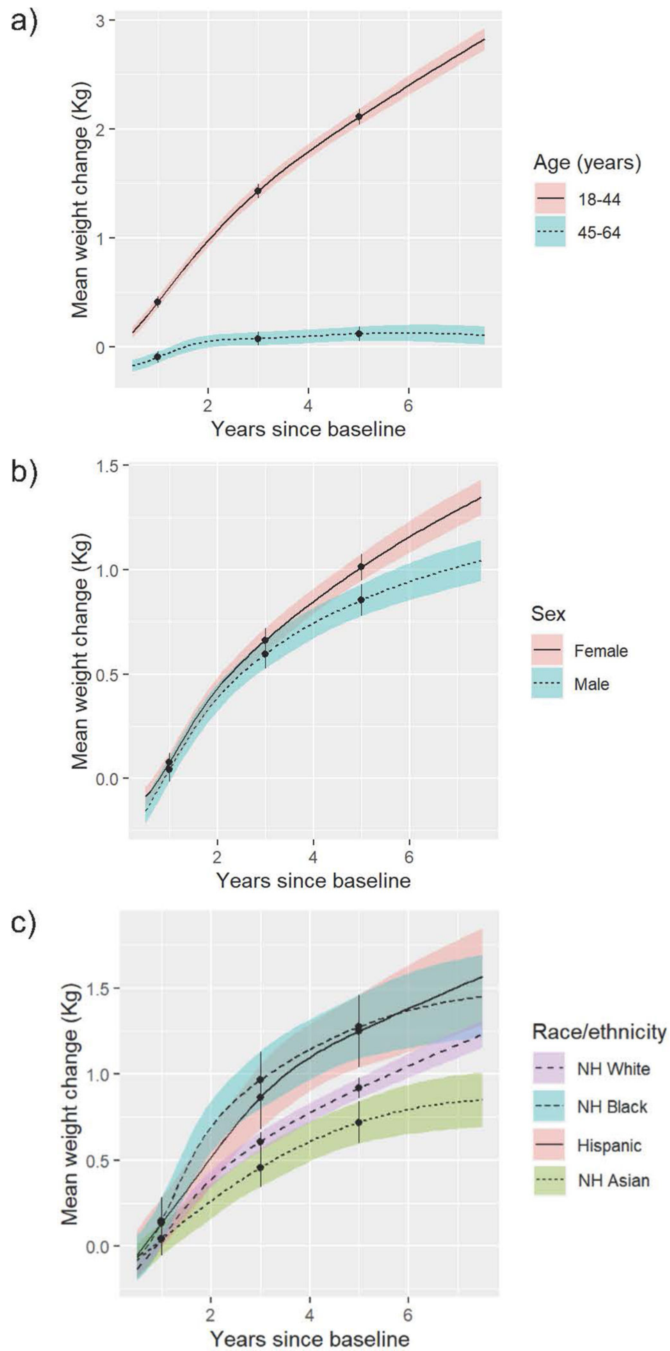

Figure 2.

Mean difference in weight change from baseline by age (a), sex (b), and race/ethnicity (c)

NH = non-Hispanic

Table 1.

Baseline characteristics, mean BMI, and obesity prevalence

Characteristic	Sample size	%	BMI	Obese
			Mean (SD)	%
Overall cohort	1,15,260	100.0	27.8 (6.6)	28.7
Sex				
Female	69,384	60.2	27.6 (7.1)	28.0
Male	45,876	39.8	28.2 (5.7)	29.8
Age categories (years)				
18–44	61,381	53.3	26.9 (6.6)	23.9
45–64	53,879	46.7	28.8 (6.5)	34.1
Race/ethnicity				
NH White	77,398	67.2	27.9 (6.6)	29.3
NH Black	8,403	7.3	30.3 (7.6)	43.5
Hispanic	7,017	6.1	28.9 (6.7)	35.6
Asian	17,578	15.3	25.2 (4.6)	13.3
Medicaid insurance				
Yes	1,273	3.6	27.3 (6.5)	26.0
No	1,13,987	96.4	27.8 (6.6)	28.8
Property value				
Decile 1	11526	10.0	29.5 (7.8)	38.6
Decile 2	11526	10.0	28.6 (7.3)	33.7
Decile 3	11411	9.9	29.0 (7.1)	35.9
Decile 4	11526	10.0	28.6 (6.9)	33.9
Decile 5	11411	9.9	28.2 (6.5)	31.6
Decile 6	11526	10.0	27.7 (6.3)	28.0
Decile 7	11526	10.0	27.3 (6.1)	25.2
Decile 8	11526	10.0	27.0 (5.8)	23.6
Decile 9	11526	10.0	26.4 (5.3)	20.0
Decile 10	11526	10.0	25.8 (5.0)	16.7

BMI = body mass index, SD = standard deviation, NH = non-Hispanic

Note: Property values are at the tax parcel level, year-specific, and inflation-adjusted to 2017 US dollars. Hawai’ian/Pacific Islander, Native American/Alaskan Native as well as multiracial, and other racial/ethnic categories were excluded from the analysis due to small sample size; therefore, racial/ethnic subgroup sample sizes will not sum to the total sample size

Table 2.

Mean difference in weight (kg) change at 1, 3, and 5 years from baseline comparing the 3rd to the 1st tertile of population, residential unit, and road intersection densities as well as fast food restaurant and supermarket counts across age strata

BE characteristic	1 year			3 years			5 years		
Subgroup sthratha	**Mean difference in weighth change (kg)**	**95% CI**	**P-value for interacthion**	**Mean difference in weighth change (kg)**	**95% CI**	**P-value for interacthion**	**Mean difference in weighth change (kg)**	**95% CI**	**P-value for interacthion**
Population density (800 m)									
18–44 years	−0.17**	(−0.30, −0.04)	0.731	−0.34***	(−0.51, −0.18)	0.215	−0.33***	(−0.52, −0.15)	0.409
45–64 years	−0.20**	(−0.33, −0.07)		−0.21**	(−0.36, −0.06)		−0.44***	(−0.60, −0.27)	
Residential density (800 m)									
18–44 years	−0.14*	(−0.26, −0.01)	0.251	−0.34***	(−0.50, −0.17)	0.402	−0.28**	(−0.47, −0.09)	0.438
45–64 years	−0.24***	(−0.37, −0.11)		−0.24**	(−0.39, −0.09)		−0.38***	(−0.54, −0.21)	
Road intersection density (800 m)									
18–44 years	−0.09	(−0.22, 0.03)	0.985	−0.27***	(−0.43, −0.11)	0.187	−0.24**	(−0.42, −0.05)	0.964
45–64 years	−0.09	(−0.22, 0.04)		−0.12	(−0.27, 0.03)		−0.23**	(−0.39, −0.07)	
Fast food count (5,000 m)									
18–44 years	−0.03	(−0.16, 0.10)	0.018	−0.28***	(−0.44, −0.11)	0.718	−0.41***	(−0.60, −0.23)	0.534
45–64 years	−0.25***	(−0.38, −0.12)		−0.32***	(−0.47, −0.17)		−0.34***	(−0.50, −0.17)	
Supermarket count (5,000 m)									
18–44 years	−0.12	(−0.25, 0.01)	0.167	−0.32***	(−0.48, −0.15)	0.570	−0.49***	(−0.68, −0.31)	0.166
45–64 years	−0.25***	(−0.38, −0.12)		−0.25***	(−0.40, −0.10)		−0.32***	(−0.49, −0.16)	

CI = confidence interval

Note: All densities are calculated as units per hectare. Population, residential, and road intersection densities are based on Euclidean distance. Fast food restaurant and supermarket counts are based on network-based buffers. Models adjust for sex (male and female), race/ethnicity (non-Hispanic White, non-Hispanic Black, Hispanic, non-Hispanic Asian, Hawai'ian/Pacific Islander, Native American/

Alaska Native, and other), Medicaid (yes/no), baseline weight (nonlinearly via spline terms with 5 DF, allowing the association to differ by age), and residential property values. Property values are at the tax parcel level, year-specific, and inflation-adjusted to 2017 US dollars. Separate models were fit for each built environment variable. P-values for interaction are Wald's tests comparing the change in weight from baseline to 1, 3, or 5 years comparing the 3rd to the 1st tertile of each built environment metric across age groups.

* P-value<0.05

** P-value<0.01

*** P-value<0.001.

These P-values are Wald's tests indicating a significant difference between the change in weight from baseline to 1, 3, or 5 years comparing the 3rd to the 1st tertile of each built environment metric.

Table 3.

Mean difference in weight (kg) change at 1, 3, and 5 years from baseline comparing the 3rd to the 1st tertile of population, residential unit, and road intersection densities as well as fast food restaurant and supermarket counts across sex strata

BE characteristic	1 year			3 years			5 years		
Subgroup strata	**Mean difference in weight change (kg)**	**95% CI**	**P-value for interaction**	**Mean difference in weight change (kg)**	**95% CI**	**P-value for interaction**	**Mean difference in weight change (kg)**	**95% CI**	**P-value for interaction**
Population density (800 m)									
Female	−0.16**	(−0.28, −0.05)	0.094	−0.17*	(−0.31, −0.03)	0.116	−0.17*	(−0.34, −0.01)	<0.001
Male	−0.32***	(−0.46, −0.17)		−0.35***	(−0.52, −0.17)		−0.60***	(−0.79, −0.41)	
Residential density (800 m)									
Female	−0.19**	(−0.30, −0.07)	0.209	−0.19**	(−0.33, −0.05)	0.130	−0.17*	(−0.33, −0.01)	0.011
Male	−0.30***	(−0.45, −0.16)		−0.36***	(−0.53, −0.19)		−0.49***	(−0.68, −0.30)	
Road intersection density (800 m)									
Female	−0.14*	(−0.26, −0.03)	0.463	−0.18*	(−0.32, −0.04)	0.848	−0.09	(−0.25, 0.07)	0.010
Male	−0.07	(−0.22, 0.07)		−0.16	(−0.33, 0.01)		−0.40***	(−0.59, −0.21)	
Fast food count (5,000 m)									
Female	−0.17**	(−0.29, −0.05)	0.973	−0.26***	(−0.40, −0.11)	0.775	−0.18*	(−0.34, −0.01)	0.002
Male	−0.18*	(−0.32, −0.03)		−0.29***	(−0.46, −0.12)		−0.56***	(−0.74, −0.37)	
Supermarket count (5,000 m)									
Female	−0.22***	(−0.34, −0.11)	0.671	−0.28***	(−0.43, −0.14)	0.755	−0.27***	(−0.43, −0.11)	0.031
Male	−0.18*	(−0.33, −0.04)		−0.25**	(−0.42, −0.08)		−0.54***	(−0.73, −0.35)	

CI = confidence interval

Note: All densities are calculated as units per hectare. Population, residential, and road intersection densities based on Euclidean distance. Fast food restaurant and supermarket counts are based on network-based buffers. Models adjust for age (18–44 years, 45–64 years), race/ethnicity (non-Hispanic White, non-Hispanic Black, Hispanic, non-Hispanic Asian, Hawai'ian/Pacific Islander, Native American/Alaska Native, other), Medicaid (yes/no), baseline weight (nonlinearly via spline terms with 5 DF, allowing association to differ by sex), and residential property values. Property values are at the tax parcel level, year-specific, and inflation-adjusted to 2017 US dollars. Separate models were fit for each built environment variable. P-values for interaction are Wald's tests comparing the change in weight from baseline to 1, 3, or 5 years comparing the 3rd to the 1st tertile of each built environment metric across sex.

* P-value<0.05

** P-value<0.01

*** P-value<0.001.

These P-values are Wald's tests indicating a significant difference between the change in weight from baseline to 1, 3, or 5 years comparing the 3rd to the 1st tertile of each built environment metric.

Table 4.

Mean difference in weight (kg) change at 1, 3, and 5 years from baseline comparing the 3rd to the 1st tertile of population, residential unit, and road intersection densities as well as fast food restaurant and supermarket counts across racial/ethnic strata

BE characteristic	1 year			3 years			5 years		
Subgroup strata	**Mean difference in weight change (kg)**	**95% CI**	**P-value for interaction**	**Mean difference in weight change (kg)**	**95% CI**	**P-value for interaction**	**Mean difference in weight change (kg)**	**95% CI**	**P-value for interaction**
Population density (800 m)									
NH White	−0.29***	(−0.40, −0.18)	0.005	−0.31***	(−0.45, −0.18)	0.082	−0.52***	(−0.66, −0.37)	<0.001
NH Black	−0.02	(−0.38, 0.34)		−0.31	(−0.76, 0.14)		−0.73**	(−1.24, −0.23)	
Hispanic	0.37*	(0.00, 0.75)		0.2	(−0.28, 0.67)		0.39	(−0.16, 0.93)	
NH Asian	−0.22	(−0.46, 0.03)		−0.04	(−0.33, 0.26)		0.23	(−0.10, 0.56	
Residential density (800 m)									
NH White	−0.30***	(−0.41, −0.19)	0.020	−0.36***	(−0.49, −0.23)	0.001	−0.47***	(−0.61, −0.32)	<0.001
NH Black	0.06	(−0.30, 0.42)		−0.62**	(−1.07, −0.17)		−0.86***	(−1.37, −0.36)	
Hispanic	0.21	(−0.16, 0.59)		0.12	(−0.36, 0.59)		0.10	(−0.46, 0.65)	
NH Asian	−0.19	(−0.44, 0.06)		0.18	(−0.13, 0.48)		0.44*	(0.10, 0.78)	
Road intersection density (800 m)									
NH White	−0.12*	(−0.23, −0.01)	0.034	−0.23***	(−0.36, −0.10)	<0.001	−0.34***	(−0.49, −0.19)	<0.001
NH Black	−0.21	(−0.55, 0.12)		−0.83***	(−1.25, −0.41)		−1.01***	(−1.48, −0.55)	
Hispanic	0.19	(−0.18, 0.56)		0.36	(−0.11, 0.83)		0.32	(−0.21, 0.86)	
NH Asian	−0.18	(−0.42, 0.06)		0.09	(−0.19, 0.37)		0.25	(−0.06, 0.57)	
Fast food count (5,000 m)									
NH White	−0.20***	(−0.32, −0.09)	0.308	−0.37***	(−0.50, −0.24)	0.021	−0.46***	(−0.61, −0.32)	0.005
NH Black	−0.24	(−0.59, 0.12)		−0.48*	(−0.92, −0.03)		−0.54*	(−1.03, −0.05)	
Hispanic	0.17	(−0.22, 0.56)		0.12	(−0.37, 0.60)		0.19	(−0.37, 0.75)	
NH Asian	−0.15	(−0.40, 0.10)		0.03	(−0.27, 0.32)		0.05	(−0.27, 0.37)	
Supermarket count (5,000 m)									
NH White	−0.26***	(−0.37, −0.15)	0.082	−0.35***	(−0.48, −0.22)	0.006	−0.53***	(−0.67, −0.38)	<0.001

BE characteristic	1 year			3 years			5 years		
Subgroup strata	**Mean difference in weight change (kg)**	**95% CI**	**P-value for interaction**	**Mean difference in weight change (kg)**	**95% CI**	**P-value for interaction**	**Mean difference in weight change (kg)**	**95% CI**	**P-value for interaction**
NH Black	−0.25	(−0.60, 0.10)		−0.58**	(−1.02, −0.14)		−0.67**	(−1.16, −0.18)	
Hispanic	0.19	(−0.19, 0.57)		0.12	(−0.36, 0.59)		0.35	(−0.20, 0.89)	
NH Asian	−0.07	(−0.32, 0.18)		0.09	(−0.20, 0.38)		0.16	(−0.16, 0.48)	

CI = confidence interval; NH = non-Hispanic

Note: All densities are calculated as units per hectare. Population, residential, and road intersection densities are based on Euclidean distance. Fast food and supermarket counts are based on network-based buffers. Models adjust for age (18–44 years, 45–64 years), sex (male and female), Medicaid (yes/no), baseline weight (nonlinearly via spline terms with 5 DF, allowing association to differ by race/ethnicity), and residential property values. Hawai’ian/Pacific Islander, Native American/Alaskan Native as well as multiracial, and other racial/ethnic categories were excluded from the analysis due to small sample size. Property values are at the tax parcel level, year-specific, and inflation-adjusted to 2017 US dollars. Separate models were fit for each built environment variable. P-values for interaction are Wald's tests comparing the change in weight from baseline to 1, 3, or 5 years comparing the 3rd to the 1st tertile of each built environment metric across racial/ethnic groups.

* P<0.05

** P<0.01

*** P<0.001.

These P-values are Wald's tests indicating a significant difference between the change in weight from baseline to 1, 3, or 5 years. comparing the 3rd to the 1st tertile of each built environment metric.