Supplemental Table 1. Built environment characteristic temporal match based on baseline year of cohort entry and available data

Baseline year of entry	Population density	Residential unit density	Road intersection density	Fast food restaurant count	Supermarket count	Residential property values
2005	2000	2005	2010	2008	2008	2005
2006	2010	2006	2010	2008	2008	2006
2007	2010	2007	2010	2008	2008	2007
2008	2010	2008	2010	2008	2008	2008
2009	2010	2009	2010	2008	2008	2009
2010	2010	2010	2010	2008	2008	2010
2011	2011	2011	2011	2012	2012	2011
2012	2012	2012	2012	2012	2012	2012
2013	2013	2013	2013	2012	2012	2013
2014	2014	2014	2014	2015	2015	2014
2015	2015	2015	2015	2015	2015	2015
2016	2016	2016	2016	2015	2015	2016
2017	2017	2017	2017	2015	2015	2017

Note: Residential unit density and residential property values data was available yearly, for all other built environment characteristics, patients were matched to next available data based on their entry into the cohort.

Supplemental Table 2. Built environment characteristics and their relationship with change in weight (in kilograms) at 1, 3, and 5 years from baseline (mean difference), after adjusting for baseline demographics, weight, year-specific patient property values at the tax parcel level, smoking status, and comorbidities

Built environment characteristic	1 year		3 year		5 year	
	Wt. Change (95% CI)	***P*-value**	**Wt. Change (95% CI)**	***P*-value**	**Wt. Change (95% CI)**	***P*-value**
Overall	0.06 (0.01, 0.10)		0.65 (0.60, 0.70)		0.97 (0.91, 1.02)	
Population density tertiles (800 m)						
Tertile 1 (0.0 to <15.8)	0.16 (0.09, 0.23)		0.76 (0.68, 0.85)		1.10 (1.01, 1.20)	
Tertile 2 (15.8 to <26.0)	0.05 (-0.02, 0.12)		0.63 (0.54, 0.71)		0.93 (0.83, 1.02)	
Tertile 3 (26.0 to 129.5)	-0.06 (-0.13, 0.02)	<0.001	0.55 (0.45, 0.64)	<0.001	0.85 (0.74, 0.96)	<0.001
Residential unit density tertiles (800 m)						
Tertile 1 (0.0 to <6.4)	0.15 (0.08, 0.22)		0.73 (0.65, 0.82)		1.03 (0.94, 1.12)	
Tertile 2 (6.4 to <11.5)	0.08 (0.01, 0.15)		0.69 (0.61, 0.78)		1.02 (0.92, 1.12)	
Tertile 3 (11.5 to 123.3)	-0.08 (-0.16, -0.01)	<0.001	0.50 (0.40, 0.59)	<0.001	0.82 (0.71, 0.93)	0.004
Transit threshold for residential unit density (800 m)[a]						
0.0 to <18.0	0.09 (0.04, 0.13)		0.69 (0.64, 0.75)		0.99 (0.93, 1.05)	
18.0 to 123.0	-0.16 (-0.27, -0.04)	<0.001	0.31 (0.15, 0.47)	<0.001	0.75 (0.55, 0.95)	0.018
Road intersection density tertiles (800 m)						
Tertile 1 (0.0 to <0.5)	0.10 (0.03, 0.17)		0.70 (0.62, 0.79)		1.04 (0.95, 1.14)	
Tertile 2 (0.5 to <0.7)	0.08 (0.01, 0.16)		0.73 (0.64, 0.82)		0.97 (0.87, 1.07)	
Tertile 3 (0.7 to 1.9)	-0.02 (-0.09, 0.05)	0.020	0.51 (0.42, 0.60)	0.003	0.88 (0.78, 0.98)	0.020
Fast food count (1,600 m)						
None	0.12 (0.05, 0.18)		0.68 (0.60, 0.76)		0.98 (0.89, 1.07)	
Any	0.02 (-0.04, 0.07)	0.021	0.63 (0.56, 0.70)	0.300	0.96 (0.88, 1.03)	0.650
Fast food count tertiles (5,000 m)						
Tertile 1 (0 to <14)	0.13 (0.06, 0.21)		0.76 (0.67, 0.85)		1.13 (1.03, 1.23)	
Tertile 2 (14 to <28)	0.09 (0.02, 0.16)		0.71 (0.62, 0.79)		0.99 (0.89, 1.08)	
Tertile 3 (28 to 99)	-0.06 (-0.13, 0.02)	<0.001	0.47 (0.37, 0.56)	<0.001	0.76 (0.65, 0.86)	<0.001
Supermarket count (1,600 m)						
None	0.11 (0.05, 0.17)		0.69 (0.62, 0.77)		0.99 (0.90, 1.07)	
Any	0.01 (-0.05, 0.07)	0.017	0.61 (0.54, 0.68)	0.110	0.95 (0.87, 1.03)	0.530
Supermarket count tertiles (5,000 m)						
Tertile 1 (0 to <5)	0.16 (0.09, 0.24)		0.79 (0.70, 0.88)		1.11 (1.01, 1.21)	
Tertile 2 (5 to <9)	0.08 (0.01, 0.15)		0.69 (0.61, 0.78)		1.05 (0.95, 1.15)	
Tertile 3 (9 to 26)	-0.07 (-0.14, 0.00)	<0.001	0.48 (0.40, 0.57)	<0.001	0.75 (0.65, 0.85)	<0.001

Wt = weight, CI = confidence interval

Note: All densities are calculated as units per hectare. Population, residential, and road intersection densities based on Euclidean distance. Fast food and supermarket counts based on network-based buffer. Models adjust for sex (male and female), baseline age (nonlinearly via spline terms with 10 DF), 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 association to differ by gender), and patient residential property values at the tax parcel level, smoking status, and comorbid conditions. Separate model fit for each BE variable. Models for fast food and supermarket counts at 1600m are binary comparisons of any vs. none, not tertiles. *P*-values compare 1, 3, and 5-year weight change between the third and first tertile (or any versus none for binary variables).

[a]Transit threshold refers to the residential unit density needed to support development of transit systems

Supplemental Table 3. Built environment characteristics and their relationship with change in weight (in kilograms) at 1, 3, and 5 years from baseline adjusting for baseline demographics and weight

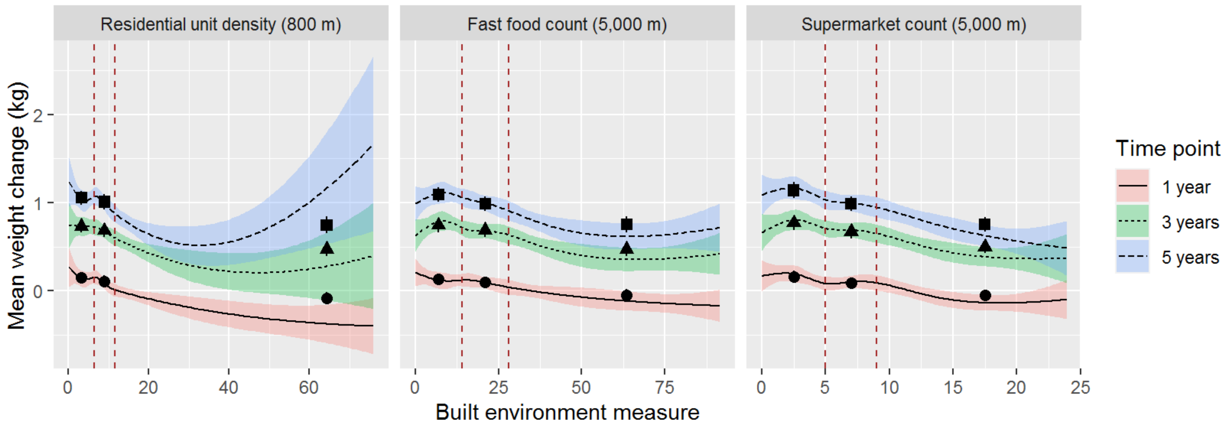
Built environment characteristic	**1 year**		**3 year**		**5 year**	
	Wt. Change (95% CI)	***P*-value**	**Wt. Change (95% CI)**	***P*-value**	**Wt. Change (95% CI)**	***P*-value**
Overall	0.23 (0.19, 0.26)	--	0.77 (0.73, 0.81)	--	1.05 (1.00, 1.10)	--
Population density tertiles (800 m)						
Tertile 1 (0.0 to <15.8)	0.25 (0.19, 0.32)		0.82 (0.75, 0.90)		1.16 (1.07, 1.24)	
Tertile 2 (15.8 to <26.0)	0.20 (0.14, 0.27)		0.75 (0.68, 0.83)		1.03 (0.95, 1.12)	
Tertile 3 (26.0 to 129.5)	0.22 (0.15, 0.28)	0.410	0.73 (0.65, 0.81)	0.100	0.94 (0.85, 1.03)	<0.001
Residential unit density tertiles (800 m)						
Tertile 1 (0.0 to <6.4)	0.22 (0.16, 0.29)		0.79 (0.72, 0.86)		1.08 (1.00, 1.16)	
Tertile 2 (6.4 to <11.5)	0.26 (0.19, 0.32)		0.81 (0.74, 0.89)		1.11 (1.03, 1.20)	
Tertile 3 (11.5 to 123.3)	0.19 (0.13, 0.26)	0.500	0.69 (0.61, 0.78)	0.083	0.92 (0.83, 1.01)	0.008
Transit threshold for residential unit density (800 m)[a]						
0.0 to <18.0	0.22 (0.18, 0.26)		0.78 (0.73, 0.83)		1.06 (1.01, 1.11)	
18.0 to 123.0	0.23 (0.13, 0.34)	0.860	0.65 (0.51, 0.80)	0.087	0.89 (0.71, 1.06)	0.049
Road intersection density tertiles (800 m)						
Tertile 1 (0.0 to <0.5)	0.22 (0.16, 0.28)		0.79 (0.71, 0.86)		1.10 (1.01, 1.18)	
Tertile 2 (0.5 to <0.7)	0.24 (0.17, 0.30)		0.81 (0.74, 0.89)		1.08 (1.00, 1.17)	
Tertile 3 (0.7 to 1.9)	0.22 (0.16, 0.29)	0.980	0.71 (0.63, 0.78)	0.140	0.95 (0.86, 1.04)	0.018
Fast food count (1,600 m)						
None	0.22 (0.16, 0.28)		0.76 (0.69, 0.83)		1.06 (0.98, 1.14)	
Any	0.23 (0.18, 0.28)	0.790	0.78 (0.72, 0.84)	0.590	1.04 (0.97, 1.10)	0.630
Fast food count tertiles (5,000 m)						
Tertile 1 (0 to <14)	0.21 (0.15, 0.28)		0.81 (0.73, 0.89)		1.14 (1.05, 1.22)	
Tertile 2 (14 to <28)	0.25 (0.19, 0.32)		0.82 (0.74, 0.89)		1.09 (1.01, 1.17)	
Tertile 3 (28 to 99)	0.20 (0.14, 0.27)	0.810	0.67 (0.59, 0.75)	0.009	0.90 (0.81, 0.99)	<0.001
Supermarket count (1,600 m)						
None	0.24 (0.18, 0.29)		0.78 (0.72, 0.85)		1.08 (1.01, 1.15)	
Any	0.22 (0.17, 0.27)	0.580	0.76 (0.70, 0.82)	0.550	1.02 (0.95, 1.09)	0.220
Supermarket count tertiles (5,000 m)						
Tertile 1 (0 to <5)	0.27 (0.20, 0.34)		0.86 (0.78, 0.94)		1.20 (1.11, 1.29)	
Tertile 2 (5 to <9)	0.22 (0.15, 0.28)		0.77 (0.70, 0.85)		1.06 (0.98, 1.15)	
Tertile 3 (9 to 26)	0.20 (0.14, 0.26)	0.098	0.69 (0.62, 0.77)	0.002	0.90 (0.82, 0.99)	<0.001

Wt = weight, CI = confidence interval

Note: All densities are calculated as units per hectare. Population, residential, and road intersection densities based on Euclidean distance. Fast food and supermarket counts based on network-based buffer. Models adjust for sex (male and female), baseline age (nonlinearly via spline terms with 10 DF), 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), and baseline weight (nonlinearly via spline terms with 5 DF, allowing association to differ by gender). Separate model fit for each BE variable. Models for fast food and supermarket counts at 1600m are binary comparisons of any vs. none, not tertiles. *P*-values compare 1, 3, and 5-year weight change between the third and first tertile (or any versus none for binary variables).

[a]Transit threshold refers to the residential unit density needed to support development of transit systems

Supplemental Figure 1. Continuous built environmental exposure-response function for residential unit density (800 m), fast food count (5,000 m), and supermarket count (5,000 m).



Note: Points correspond to estimates from main model of BE using tertiles (vertical lines correspond to the 1/3 and 2/3 percentiles). Because BE measures are skewed right, plots are truncated at the upper 99.5th percentile of the distribution of each BE measure.

TECHNICAL APPENDIX

Residential property values

Since the electronic medical record (EMR) does not contain traditional measures of socioeconomic status (SES) (e.g. income, education), we used patient residential property values at the tax parcel level as a proxy measure for SES. Prior health and social sciences research have demonstrated that residential property values are highly correlated with individual as well as area-level measures of SES and are predictive of health [1–9]. Residential property values are the smallest unit of geographic disaggregation and reflect the combined relative, local value of a given home and the land it rests on [8]. They can also serve as an aggregate measure of neighborhood characteristics [8]. Moreover, residential property values are advantageous as they offer a flexible, geo-localized measure of SES that is available in many areas of the US and the world and updated regularly [8].

Our patient residential property value data came from the KC assessor's tax parcel data. The value per residential unit was obtained by dividing the assessed value by the number of units at that parcel, adjusted for inflation to 2017 US dollars, using the Consumer Price Index. "Implausible" values defined as <$10,000 were excluded. This cut point was used to exclude properties whose assessed value was implausibly low or $0. Approximately 87% of excluded values were $0. The data were then categorized into calendar year-specific deciles, given that patients entered the cohort at different times.

SmartMaps

Euclidean-based SmartMaps

Euclidean-based SmartMaps (residential unit, population, and intersection density) were created with focal processing methods in PostgreSQL/PostGIS and R [10,11]. Whereas typical GIS measurement processes create BE summaries using vector-based overlay methods for buffers around single points of interest, SmartMaps front-load the GIS analysis, essentially calculating these summaries for all locations across the study area. For example, the residential unit density SmartMap is created by first establishing a 30 x 30 m grid of cells or mesh points representing the study area. Second, each 30 x 30 m cell in a parcel polygon is assigned an estimate of the number of residential units within the cell (e.g., a 9,000 m^2 parcel with 20 residential units would result in 10 cells each containing 2 units). Finally, a "focal sum" process is used to visit every study area cell or mesh point, selecting those cells that are within the specified radius of the mesh point, summing the count of residential units in those cells, and placing the sum value as an attribute of the cell or mesh point, repeating the process for each mesh point. This method is operationally more efficient than a vector-based approach in assigning values of the local environment to large numbers of points that represent respondents home, work, or activity locations. It can do so by creating a data set that represents spatially continuous values over the entire study area [12–15]. Efficiency is achieved by relying on focal processes within the GIS software, which effectively front-loads the generation of neighborhood-level summaries at every location within the study area in a single process, whereas the traditional vector-based method repeats a work flow at each geocoded home location. Spatial continuity confers the ability to measure each built environment variable using the SmartMap and any set of points by employing the R raster getValues() function or the SurfaceSpot method in ArcGIS [10,11]. Importantly, this has meant that the SmartMap data could first be created by GIS analysts outside KPW and then transferred to KPW staff, who could perform the final measurement step without requiring patient addresses to be accessed outside the KPW firewall.

Network-based SmartMaps

Counts of supermarket and fast food/quick service facilities within specified distances of home geocodes were generated using network-based SmartMaps of the food environment developed from geocoded food permit addresses from Public Health-Seattle KC [3,15–17]. These SmartMaps were created by generating network “service area” buffers around each food outlet. First, all streets accessible within the target distance were identified using the pgRouting pgr_drivingdistance() function applied to OpenStreetMap data. The end points of these streets were used to generate a “concave hull” using PostGIS (with the ST_ConcaveHull() function and a target_percent 0.99). The service area polygon layer for each food source type was then rasterized with the gdal_rasterize() function to sum any overlapping service areas. For example, if a subject resided in a location within the specified network distance of three supermarkets, the supermarket count would be three. This method is more efficient than measuring the network distance between the geocoded home and food outlet locations—which typically identifies only the closest facility. It is also more efficient than generating service areas for each home location and tabulating the count of food sources within the home-based service areas (due to the relatively large number of home geocodes and the small number of food sources). Moreover, this method, which required generating network service areas for 1,519 food places, is more efficient than generating service areas for each of the 115,260 home locations and tabulating the count of food sources within the home-based service areas.

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