Published in final edited form as:

Health Place. 2015 May ; 33: 9–18. doi:10.1016/j.healthplace.2015.01.004.

Combined measure of neighborhood food and physical activity environments and weight-related outcomes: the CARDIA Study

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Abstract

Engagement in healthy lifestyle behaviors likely reflects access to a diverse and synergistic set of food and physical activity resources, yet most research examines discrete characteristics. We characterized neighborhoods with respect to their composition of features, and quantified associations with diet, physical activity (PA), body mass index (BMI), and insulin resistance (IR) in a longitudinal biracial cohort (n=4,143; aged 25–37; 1992–2006). We used latent class analysis to derive population-density-specific (< vs. 1,750 people per sq km) clusters of neighborhood indicators: road connectivity, parks and PA facilities, and food stores/restaurants. In lower population density areas, a latent class with higher food and PA resource diversity (relative to other clusters) was significantly associated with higher diet quality. In higher population density areas, a cluster with relatively more natural food/specialty stores; fewer convenience stores; and more PA resources was associated with higher diet quality. Neighborhood clusters were inconsistently associated with BMI and IR, and not associated with fast food consumption, walking, biking, or running.

Keywords

Neighborhood; environment; diet; physical activity; obesity; insulin resistance

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The authors have no financial or other conflicts of interest to disclose.

Katie Meyer and Penny Gordon-Larsen had full access to all of the data in the study and take responsibility for the integrity of the data and the accuracy of data analysis.

Introduction

There is growing recognition that examination of comprehensive neighborhood environments may enhance our understanding of how the built environment influences weight-related health outcomes. This perspective is reflected in proposals for a broad framework around intervention design and policy development.^{1–3} Researchers have begun using observational studies to identify variables that reflect the impact of a combination of resources, including the development of measures based on hypothetical considerations of what constitutes a “healthy” environment^{4,5} or the use of data-driven, multivariate statistical methods (such as latent class analysis or factor analysis).^{6–8}

Some, though not all, of these studies indicate that considering the balance or combination of resources may be theoretically and empirically important to understanding the influence of the built environment on health behavior. To our knowledge, however, no study has included the full range of resources facilitating physical activity and food access—to best characterize neighborhoods within which people live—along with dietary, physical activity, and cardiometabolic outcomes in the same analysis. Furthermore, published examples have generally relied on cross-sectional data.^{4–8}

Using 13 years of follow-up data in a biracial cohort, we used latent class analysis (LCA) to characterize neighborhoods with respect to multiple aspects of the built environment, including the road network, the presence of parks, and the composition of physical activity and food resources. We quantified longitudinal associations between derived clusters of built environment features and individual-level dietary behaviors, physical activity, body mass index (BMI), and homeostasis model assessment of insulin resistance (HOMA-IR). We hypothesized that participants living in neighborhoods characterized by high street connectivity, a large number of parks and PA facilities, and relatively more grocery stores than convenience stores and fewer fast food establishments consume a higher quality diet and fewer fast food meals; engage in more frequent walking, running, and biking; and have lower BMI and HOMA-IR scores, as compared to participants living in neighborhoods with lower road connectivity, fewer parks and PA facilities, and a food environment composition characterized by relatively more convenience stores and fast food establishments.

Methods

Study sample

CARDIA is a multicenter, longitudinal study of cardiometabolic risk starting in young adulthood.⁹ The study began in 1985–86 with 5,115 black and white adults aged 18–30 years sampled from four metropolitan areas (Birmingham, AL; Chicago, IL; Minneapolis, MN; and Oakland, CA). A majority of the surviving cohort has been examined at follow-up examinations in 1987–1988 (year 2), 1990–1991 (year 5), 1992–1993 (year 7), 1995–1996 (year 10), 2000–2001 (year 15), and 2005–2006 (year 20) (91%, 86%, 81%, 79%, 74%, and 72% retention, respectively). Participant home addresses have been geocoded for years 0, 7, 10, 15, and 20. All exposure and outcome variables were measured at each CARDIA exam, with the exception of diet history, which was assessed at years 0, 7, and 20. We restricted

the present analysis to exam years 7, 10, 15, and 20 for comparability of food and physical activity resource data (as described in *Food and physical activity resources* below). CARDIA was approved by institutional review boards of each field center; each study participant provided informed written consent.

Individual-level measures

Diet quality—We used an *a priori* diet quality score described in previous publications as a measure of diet quality.¹⁰ In brief, at years 0, 7, and 20 participants completed an interviewer-administered validated diet history¹¹ of past-month food consumption. Using a food grouping system created by the University of Minnesota Nutrition Coordinating Center (NCC), foods were classified into 158 food groups.

We further collapsed the 158 food groups into 46 food groups as previously described¹⁰. From these 46 food groups, we created the *a priori* dietary quality score by classifying foods groups as beneficial (n=20), adverse (n=13), or neutral (n=13) based on their hypothesized influence on health. For each person, consumption quintile values were summed across the 33 non-neutral food groups with beneficial foods scored 0 to 4 (from lowest to highest consumption) and adverse foods scored 4 to 0 (from lowest to highest consumption). Thus, the score may range from 0 to 134, with higher scores indicate higher hypothesized diet quality. This diet score has been associated with health outcomes.^{10,12}

Fast food consumption—Weekly frequency of fast food consumption was assessed at all years with the question: “How many times in a week or month do you eat breakfast, lunch, or dinner in a place such as McDonald’s, Burger King, Wendy’s, Arby’s, Pizza Hut, or Kentucky Fried Chicken?” Monthly frequencies were converted to times per week.

Physical activity—Physical activity was assessed at each study examination with the validated interview-administered CARDIA Physical Activity History¹³. Participants reported their engagement in 13 activities, of which we focused on walking, running, and biking, which we hypothesized to be most relevant to the built environment features reflected in our data. We created separate indicators for weekly frequency of walking, running/jogging, and biking.¹³

Clinical outcome measures—Height and weight were measured by trained study staff at each clinical examination and recorded to the nearest 0.5 cm and 0.2 kg, respectively. Body mass index (BMI) was defined as weight (kg) divided by height squared (m²). Fasting insulin and glucose concentrations were obtained from venous blood draws. Glucose was measured using hexokinase coupled to glucose-6-phosphate dehydrogenase. The homeostasis model assessment of insulin resistance (HOMA-IR) score was calculated as: [fasting glucose (in millimoles per liter) x fasting insulin (in microunits per liter)]/22.5. Higher scores indicated higher insulin resistance.¹⁴

Covariates—Participants provided demographic and socioeconomic information on standardized questionnaires. Participants reported their age, gender, and race at baseline and their current educational attainment (years and highest degree) at all examinations.

Neighborhood-level measures

We used data derived from the CARDIA neighborhood environment database, which includes GIS-derived variables that are temporally- and geographically-linked to participant home addresses at years 0, 7, 10, 15, and 20. We considered a wide range of food and physical activity environment characteristics to capture neighborhood heterogeneity and to achieve a more comprehensive environment assessment.

Food and physical activity establishments—We used geocoded data from a commercial listing of US businesses (Dun and Bradstreet, D&B) to identify food and physical activity establishments using Standard Industrial Classification (SIC) codes. Between CARDIA years 0 and 7, SIC codes gained specificity (increasing from 4- to 8-digit codes), and we thus restricted our analysis to years 7 through 20 to insure comparability. We calculated counts of establishments that can be reached along a 3 km road network distance from participants' home addresses. We based our use of 3-km distance on previous work in CARDIA,¹⁵ on considerations of a walkable distance, and to reflect the fact that CARDIA is an urban and suburban cohort.

Food resources included convenience stores, coops/natural food stores, specialty markets, supermarkets, grocery stores, fast food restaurants, food stands/cafeterias, and non-fast food restaurants. Physical activity resources included facilities classified in D&B as instructional, membership-based, outdoor, public fee, and public non-fee.

We sought to characterize the food environment with respect to the relative contribution of specific establishments by calculating the percentage of total resources from each resource type. We hypothesized that the relative availability of food resources would be most predictive of dietary behaviors. We did not create a similar measure for physical activity resources because we hypothesized that any physical activity resources would promote physical activity.

Parks—Public parks within 3-km circular buffers around each participant's home address were calculated with the parks component of the Environmental Systems Research Institute's (ESRI) StreetMap product.

Street connectivity—We calculated two standard indicators of street connectivity within the 1-km buffer area along the road network using ESRI's StreetMap: beta index (also called link-to-node ratio) and intersection density (intersections/area). To characterize the density of street networks (street connectivity) immediately around respondents' residences, we used a 1-km circular buffer to equalize geographic area.

Covariates—We linked population Census data to each participant, based on participants' home address at the time of the examination relative to the census year (1990 for years 7 and 10, and 2000 for years 15 and 20). We examined four census tract-level indicators: 1) percent of population at less than 150% federal poverty level, 2) median family income, 3) percent of population with less than a high school education, and 4) percent of population with a college degree.

We also estimated population density within a 3-km circular buffer around each participant's residence by calculating a weighted average population count for the block groups that fell within the buffer, weighted by the proportion of the total buffer area covered by each block group.

Statistical analysis

Latent class analysis of food and physical activity resources—We used a multivariate statistical approach, latent class analysis (LCA), to identify groups of participants based on their neighborhood features, including food establishments, physical activity resources, and street connectivity. LCA is a data-driven approach to measuring an unobserved (“latent”) construct using the statistical relations among a set of observed variables. The LCA yields distinct classes that reflect variation in levels of each observed variable included in the analysis. Latent classes, or clusters, were derived from participant-level observations that reflect the distribution of CARDIA participants.

We categorized variables for food resources, parks and physical activity facilities, and street connectivity into tertiles for the LCA to address substantial skew in variable distributions. We used PROC LCA (v. 1.3.0), a user-written command for SAS.¹⁶ PROC LCA uses the EM (expectation-maximization) algorithm for class derivation and assignment. Based on a given number of classes (assigned by the analyst), the EM algorithm begins with random assignment of participants into a class and moves through an iterative series of reclassification steps where participants are reassigned until an optimal classification is achieved for the sample (based on a reclassification statistic). Classification reflects the combination of participant values on the set of categorical variables included in the LCA, with the goal of finding classes (or clusters) of participants who are similar on the combination of attributes (here, tertile values of neighborhood features). We ran models for a range of class numbers, and selected the number of classes based on interpretability of model results and the Bayesian information criterion (BIC) statistic, a measure of model fit that includes a penalty for additional parameters. We assessed whether class structure was stable over the 4 time periods (measurement invariance) with a χ^2 likelihood ratio test that compared a model in which classes were constrained over time to a model in which classes were allowed to vary over time.¹⁷ For regression analysis, we placed participants into their best-fitting class at each exam period, defined as the class with the highest probability of membership.

We derived classes within two strata of population density (< and $\geq 1,750$ people per square km), selected on the basis of correspondence to 2.75 dwelling units per acre (U.S. mean=2.55 people per household) representative of standard residential densities observed in many suburban areas at the periphery of U.S. cities^{18,19} and close to the Federal Register definition of the interface between urbanized land and undisturbed or wild land (3 housing units per acre).²⁰ CARDIA participants were recruited at baseline from metropolitan areas, within which the majority of participants remained over follow-up, and both population density strata comprise relatively urbanized areas, based on the 2000 Census definition of 1,000 people per square mile (or roughly 400 people per square km).²¹ Neighborhood

features were entered into the LCA based on their full-sample tertile values, rather than based on tertiles assigned within strata of population density.

Regression analysis for associations between neighborhood clusters and obesity-related outcomes—

We conducted repeated-measures, random effects regression in Stata (version 13.0) to quantify associations between time-varying neighborhood clusters and weight-related outcomes within the higher and lower population density strata. We used linear regression (xtreg) to model the *a priori* diet quality score, total physical activity, BMI, and HOMA-IR; and negative binomial regression (xtnbreg) to model weekly frequency of fast food consumption. Because of the high prevalence of non-participation in walking, biking, and running, we used a two-step modeling approach to assess their associations with neighborhood classes. In the two-step model, probit regression was used to quantify the probability of any/no engagement in the activity (step 1), and linear regression was used to quantify weekly frequency among those who reported engaging in the activity (step 2).²² We ran age-adjusted models as well as models further adjusted for race, gender, study center, and participant education (maximum reported over follow-up). In separate models, we additionally adjusted for neighborhood measures of educational attainment and income. We natural log-transformed (ln) BMI and HOMA-IR to account for non-normality and limit the influence of extreme observations.

All variables were included in repeated measures regression models as time-varying except participant educational attainment, which was included in the model as the maximum reported education (in years) over the 4 exam periods. Educational attainment plateaus after year 7 and this coding, standard in CARDIA, allows us to include individuals who did not report their education on a follow-up exam and removes some reported non-monotonic changes over exam cycles (i.e., apparent declines in years attained). As described, the CARDIA diet history assessment was conducted in years 7 and 20, and analyses of dietary quality were limited to those two years. Aside from diet quality, all exposure and outcome variables were measured at each of the 4 CARDIA exams included in the analysis. This includes fast food consumption, which was assessed distinctly from the diet history.

Analytic sample—Observations were excluded for exam non-attendance (n=5,276 observations over the 4 exam periods), if there were missing BMI, insulin, or glucose data (n=225 observations), the participant was pregnant at the time of the exam (n=250 observations), or was missing environment resource data (n=16). We focused on percentage measures of food resources (e.g., percent fast food restaurants among total) and we excluded observations with zero total food resources within a 3-km network buffer (n=386); to assess the sensitivity of this exclusion, we also included analysis in which we set the percentage of food resources to zero in those areas with zero total food resources. After exclusions, we had an analytic sample of 14,397 observations. Other exclusions were model- and covariate-specific, such as the lack of diet history data in years 10 and 15.

Results

Neighborhood characteristics for the study sample

Table 1 presents year-specific descriptive statistics for neighborhood variables within strata of population density. Because of substantial right skew of many variables, we present 25th, 50th, and 75th percentile values. Changes in the distribution of neighborhood resources over the study period may reflect movement of participants to new neighborhoods as well as resource changes within neighborhoods.

Latent class analysis (LCA)

Within each stratum of population density, we identified 3 neighborhood resource clusters using LCA (Figure 1). Likelihood ratio tests indicated that class structure was variable across study periods; however, because classes did not differ materially over time, we present a single 3-class model for each population density strata. Figure 1 displays stratum-specific distributions (tertiles) of built environment features by three latent classes. Due to the fact that CARDIA participants were originally recruited from urban settings and most remain in urban areas, the clusters we derived fall into strata of lower population density (<1,750 people per sq km), which is comparable to mid-size cities such as Baltimore (1,187 people per sq km), Detroit (1,078 people per sq km), and Atlanta (659 people per sq km); higher population density (>1,750 people per sq km) areas, which is comparable to larger urban areas such as Los Angeles/Long Beach/Anaheim (2,702 people per sq km), New York/Newark (2,054 people per sq km), and San Francisco/Oakland (2,419 people per sq km).²¹ Thus, both population density strata in our analysis are largely inclusive of urbanized areas.

Within each stratum of population density, we labeled clusters based on their relative relative obesogenicity (low, moderate, high) and development (low, moderate, or high). We considered, *a priori*, that obesogenic environments would be characterized as having relatively lower street connectivity, fewer physical activity facilities, and relatively higher percentages of convenience stores and fast food restaurants and relatively lower percentages of supermarkets, specialty markets, natural food stores, and non-fast food restaurants. Among the lower population density clusters, one cluster, which we labeled “low obesogenicity, moderate development,” had moderate levels of all neighborhood features, with relatively more PA resources than the other two low-population-density classes, and a diverse mix of food resources. Another cluster, “moderate obesogenicity, high development,” had high street connectivity, moderate PA resources, and high percentages of convenience stores, supermarkets, and grocery stores, relative to other food resources. The final cluster, labeled “high obesogenicity, low development,” had low street connectivity, few PA resources, and a food environment with a relatively high percentage of convenience stores and a moderate percentage of fast food establishments.

Among higher population density clusters, we note comparatively higher overall urban development than seen in the lower population density clusters. The “low obesogenicity, high development,” cluster had high street connectivity, many PA resources, and a food environment characterized by high percentages of coops, specialty markets, and non-fast

food away-from-home options and a low percentage of convenience stores. A second cluster, “moderate obesogenicity, moderate development,” had moderate levels of all features. The third cluster, “high obesogenicity, high development,” had high street connectivity, a large number of parks and other free public PA resources, convenience stores, and a high percentage of grocery stores.

Clusters differed with respect to individual- and community-level sociodemographic variables (Table 2). The distribution of covariates across clusters remained relatively stable over the study period. We note that our approach of assigning a single latent class to each participant does not incorporate the uncertainty in the latent class creation process, where participants are assigned to each cluster with varying probabilities. However, there was relatively little uncertainty in the class structure, and at least 75 percent of the sample fit into a single class with probability greater than 0.90.

Regression results

Within the lower population density stratum, the “moderate development, low obesogenicity” cluster served as referent for regression analysis; in the higher population density stratum, the “low obesogenicity, high development” class was the referent. In age-adjusted analysis, classes were significantly associated with many weight-related outcomes, but associations were attenuated and generally (with some exceptions) statistically non-significant with individual-level covariate adjustment (Table 3; Model 2). In analysis accounting for individual- and community-level covariates (Model 3), the “high obesogenicity, low development” class in the lower population density stratum, and the “moderate obesogenicity, moderate development,” and “high obesogenicity, high development” classes in the higher population density stratum, were significantly associated with lower diet quality, though magnitudes of association were modest. Fast food consumption and physical activity variables were not significantly associated with latent classes in fully-adjusted models (Model 3), while ln-BMI was positively associated with the “moderate obesogenicity, high development” class within the lower population density stratum and ln-HOMA-IR was positively associated with the “moderate obesogenicity, moderate development” class within the higher population density stratum.

Results were similar whether we excluded participants with zero total food resources within a 3-km network buffer (n=386) or set all food resource measures to zero for these participants. Given the robustness of findings, we presented only results for models that excluded participants with zero total food resources, which allowed a consistent interpretation of a zero value for relative food resource measures. It also served to exclude more rural environments, focusing our analysis on regions for which we have sufficient power.

Discussion

In a prospective biracial cohort, we applied a multivariate statistical approach (latent class analysis, LCA) to characterize neighborhoods with respect to the combination of physical activity and food resources over 13 years of follow-up. Within strata of lower and higher population density, we identified 3 types of neighborhoods characterized by clusters of built

environment features reflecting distinct combinations of street connectivity, neighborhood parks, physical activity resources, and food stores and restaurants. In multivariable-adjusted regression models, accounting for individual- and community-level covariates, neighborhood clusters were significantly associated with a measure of overall diet quality, but were not associated with fast food consumption or physical activity measures. Specifically, in lower population density neighborhoods, diet quality was positively associated with diversity in the food environment; in higher population density neighborhoods, diet quality was positively associated with a food environment with relatively more coop groceries/natural food stores and specialty markers and relatively fewer convenience stores. Some, but not all, clusters of neighborhood features were associated with BMI and HOMA-IR. To our knowledge, this is the first application of LCA to longitudinal data with the goal of quantifying associations for neighborhoods defined by physical activity and food resources on a range of weight-related outcomes.

Our findings contribute to a growing literature about how multifaceted composition of the built environment may be more informative than single resources to understanding the association between environmental variables with weight-related behaviors and outcomes.^{4,5,8,23–28} Prior publications of multivariate statistical methods have generally characterized the built environment more narrowly, focusing on a single exposure construct, such as physical activity.^{7,8,26,28} We expanded on this published work by including a broad set of neighborhood resource variables and several weight-related outcomes and by assessing longitudinal associations. An exception is Wall and colleagues, who included both physical activity and diet resources, but limited to a single outcome: BMI.⁶ In general, the density of food and physical activity resources track, reflecting the overall density of built environment features. A limited set of neighborhood features will not fully represent neighborhood structures as they exist, and analyses may be confounded given correlations among built environment features.

We note that studying comprehensive measures of the neighborhood built environment lacks the appeal of identifying a specific exposure that can be addressed more easily through policy (e.g., limiting fast food restaurants in south Los Angeles, CA),²⁹ but it may be a more accurate reflection of human behavior within a system of environmental features. The notion that the overall distribution and availability of resources may be most relevant to health is consistent with theories of behavioral economics, in which human behavior will in part reflect the mix of opportunities and costs.³⁰ Furthermore, a limitation of studying a single food resource is the possibility of confounding by the mix of available neighborhood environment options, which may help explain inconsistent findings reported in the field.²⁹

Our most consistent findings were with diet quality. These findings mirror other studies showing that the relative composition of the food environment influences dietary behavior.^{4,23–25} In a cross-sectional study of Australian adults, Mason and colleagues categorized neighborhoods in terms of the percentage of total food resources that were considered “healthy,” and found that this measure was associated with greater individual-level fruit and vegetable purchases, while the absolute numbers of “healthy” stores was not associated with fruit and vegetable purchases.⁵ Our approach addresses the need, highlighted in a recent review of the literature,²⁹ to broadly integrate features of the food environment.

It is not clear why our findings for diet were more consistent than other outcomes. We expected, *a priori*, that considering both diet and physical activity environments would help reveal features that influence outcomes related to both behaviors, such as weight and insulin resistance. One interpretation of these findings is that for CARDIA participants, neighborhood environment factors may have comparatively stronger association with diet versus physical activity behaviors. However, the lack of significant findings for physical activity behaviors with clusters of built environment features in the present analysis conflicts with reports from our group and others of positive associations for street connectivity²² and land use mix³¹ with physical activity. It is possible that the clusters of neighborhood features (as in this study) may dilute the estimated effects of individual features of the built environment (such as street connectivity). Future studies are needed to confirm our findings and inform the understanding of how complex environments may influence complex behaviors.

A general limitation of data-driven approaches to deriving multivariate groupings is that results will be sample-dependent, limiting our ability to compare results across studies. Indeed, our class structure is difficult to compare to the structure reported by Wall, et al., which also incorporated both food and physical activity resources.⁶ Other authors have used *a priori* approaches to create an index of food resources based on their hypothesized relation to health behaviors⁴. There are advantages to each method; however, given the lack of consistent associations in the literature between specific resource types and health behaviors, we elected to use a data-driven approach. Yet derivation of class labels necessitates some subjectivity and reductionism in relation to within-class diversity. A comprehensive approach to the food environment may help unravel what could be considered counter-intuitive results in the literature, such as the positive association between (farther) distance from residential locations to supermarkets with higher fruit and vegetable consumption.³² Such counter-intuitive observations could relate to the relative availability of other food shopping or eating options. For example, in the higher population density subgroup, the cluster that had relatively lower percentages of supermarkets and grocery stores (and relatively higher natural foods stores and specialty markets), had comparatively higher diet quality

A primary consideration in studies of the built environment and health is the possibility of structural confounding, resulting from non-exchangeable populations living in different neighborhoods.³³ We observed skewed individual- and community-level sociodemographic variables across latent classes, though there was adequate representation of social and demographic groups in all neighborhood clusters. Regression associations were attenuated upon adjustment for individual-level covariates (including race and education), but, in general, further control for neighborhood-level income and education did not materially change our results. Other studies have shown that the built environment differs according to neighborhood socioeconomics,^{34,35} and it is possible that we captured some such confounding through our adjustment for individual-level variables. We note that because we were interested in studying features of the built environment that have been considered for health-related policies, such as altering the food environment and the presence of neighborhood parks, we included models without adjustment for neighborhood SES, as well

as those adjusted for neighborhood SES. It is possible that residual confounding remains due to self-selection related to other, non-SES-related features of the built environment, such as employment centers or public services.^{36–38}

An important caveat is our reliance on GIS-based measures of food and physical activity resources that were within 3 kilometers of study participant residences. Our findings are limited in that we focus only on the residential neighborhood, whereas the activity space literature has shown that people spend considerable time in different spaces, such as workplaces.^{39–42} In addition, GIS measures may be less relevant to behavior than perception-based measures.²⁹ Other studies have documented errors in the D&B and other commercial databases of environmental resources.^{43,44} We hypothesize that such errors would bias results to the null value of no effect, although the potential for differential misclassification by resident characteristics has also been shown.⁴⁵ Furthermore, although we attempted to examine the relative contributions of food resources that we consider more or less conducive to healthy dietary choices, we do not know the nature of those resources in terms of their food options or affordability. We note that CARDIA participants were recruited from urban environments and that the cohort continued to primarily reflect urban and suburban regions over follow-up. This, along with our restriction of participants to those with any food store or restaurant within 3 kilometers of their residence, may limit the generalizability of our findings to rural samples.

Other strengths of our study include our use of a novel multivariate approach to characterize neighborhoods with respect to physical activity and diet resources, the prospective study design, clinic-based assessment of personal characteristics, and the geographic and sociodemographic diversity of the study sample.

Conclusion

In conclusion, in this prospective biracial adult cohort, we identified neighborhood clusters that were significantly and consistently associated with a diet quality score. Some, but not all, clusters of neighborhood features were also significantly associated with BMI and HOMA-IR, but no cluster was associated with fast food consumption or physical activity in fully adjusted models. We note that statistically significant associations were weak and further studies are needed to confirm our results. Our findings indicate that the neighborhood composition of food resources may be relevant for dietary behaviors and cardiometabolic outcomes—such as BMI and HOMA-IR.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgments

The authors would like to acknowledge CARDIA Chief Reviewer Linda Van Horn, PhD, whose thoughtful suggestions improved the paper. This work was funded by the National Heart, Lung, and Blood Institute (NHLBI) R01HL104580. The Coronary Artery Risk Development in Young Adults Study (CARDIA) is supported by contracts HHSN268201300025C, HHSN268201300026C, HHSN268201300027C, HHSN268201300028C, HHSN268201300029C, and HHSN268200900041C from the NHLBI, the Intramural Research Program of the National Institute on Aging (NIA), and an intra-agency agreement between NIA and NHLBI (AG0005). For

general support, the authors are grateful to the Carolina Population Center, University of North Carolina at Chapel Hill (grant R24HD050924 from the Eunice Kennedy Shriver National Institute of Child Health and Human Development [NICHD]), the Nutrition Obesity Research Center (NORC), University of North Carolina (grant P30DK56350 from the National Institute for Diabetes and Digestive and Kidney Diseases [NIDDK]), and the UNC Center for Environmental Health and Susceptibility (CEHS), University of North Carolina (grant P30ES010126 from the National Institute of Environmental Health Sciences [NIEHS]). NIH had no role in the design or conduct of the study; collection, management, analysis, or interpretation of the data; or preparation, review, or approval of the manuscript.

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Highlights

1. Individuals are exposed to complex neighborhood environments.
2. Most studies of weight-related outcomes focus on distinct resources.
3. We derived clusters of neighborhood resources related to diet and physical activity.
4. Clusters were associated with diet quality, but not physical activity or BMI.
5. Neighborhood resource composition may influence dietary behaviors.

a. Lower population density (< 1,750 people per sq km)

b. Higher population density ($\geq 1,750$ people per sq km)

Figure 1.

Distributions of neighborhood features (tertiles) by neighborhood clusters according to low (a) and high (b) population density. Neighborhood clusters are ordered from low to high obesogenicity within population density strata.

- a. Lower population density ($< 1,750$ people per sq km)
- b. Higher population density ($\geq 1,750$ people per sq km)

Table 1

Median and interquartile range of year-specific distributions of neighborhood features by CARDIA examination year: CARDIA 1992–2006.

Lower population density (<1,750 people per sq km)												
	Year 7 (n=1440)			Year 10 (n=1990)			Year 15 (1979)			Year 20 (n=2078)		
	25 th %	Median	75 th %	25 th %	Median	75 th %	25 th %	Median	75 th %	25 th %	Median	75 th %
Street connectivity ²												
Beta index ³	1.39	1.52	1.63	1.35	1.48	1.61	1.37	1.49	1.62	1.36	1.49	1.62
Intersection density ⁴	20.4	32.2	44.6	17.5	29.0	41.4	20.4	33.3	45.5	16.2	31.5	44.9
Physical activity resources												
Parks ⁵	1	7	11	1	6	11	1	5	11	0	4	11
Instructional PA	0	0	2	0	1	2	0	1	3	0	1	3
Membership PA	0	0	1	0	1	2	0	1	2	0	1	3
Outdoor	0	0	1	0	1	1	0	1	2	0	1	2
Public fee	0	1	2	0	1	1	0	1	2	0	1	3
Public non-fee	0	0	0	0	0	1	0	0	1	0	0	1
Food resources												
Convenience stores	3	8	13	2	6	12	2	6	12	2	6	12
Coops/natural foods	0	0	0	0	0	0	0	0	0	0	0	0
Specialty markets	0	1	4	0	2	4	0	2	4	0	2	5
Supermarkets	0	1	2	0	1	1	0	1	1	0	1	2
Grocery stores	2	4	10	1	3	6	1	4	7	1	3	7
Non-fast food restaurants	1	3	8	1	3	7	1	4	9	1	6	12
Food stands/cafeterias	3	8	15	2	9	17	3	10	18	2	6	13
Fast food restaurants	1	4	9	1	5	10	1	6	11	2	8	17

Higher population density (1,750 people per sq km)												
	Year 7 (n=2419)			Year 10 (n=1840)			Year 15 (1622)			Year 20 (n=1428)		
	25 th %	Median	75 th %	25 th %	Median	75 th %	25 th %	Median	75 th %	25 th %	Median	75 th %
Road network ²												

	Higher population density (1,750 people per sq km)											
	Year 7 (n=2419)				Year 10 (n=1840)				Year 15 (1622)			
	25 th %	Median	75 th %		25 th %	Median	75 th %		25 th %	Median	75 th %	
Beta index ³	1.75	1.85	1.96		1.72	1.83	1.95		1.70	1.82	1.94	
Intersection density ⁴	47.4	53.2	62.7		46.2	51.9	61.4		48.1	54.1	69.1	
Physical activity resources												
Parks ⁵	15	20	26		14	20	26		14	19	26	
Instructional PA	2	5	10		4	6	12		4	9	19	
Membership PA	2	4	7		2	3	6		2	3	5	
Outdoor	1	2	5		1	2	3		1	3	5	
Public fee	1	3	5		1	2	4		1	3	5	
Public non-fee	2	4	6		2	4	7		2	4	7	
Food resources												
Convenience stores	24	34	44		16	22	30		15	21	28	
Coops/natural foods	0	1	5		1	2	4		0	1	3	
Specialty markets	10	14	37		7	13	27		8	16	29	
Supermarkets	2	3	4		1	2	3		1	3	4	
Grocery stores	26	49	75		15	30.5	49		17	31	47	
Non-fast food restaurants	13	27	59		10	18	37.5		13	23	45	
Food stands/caferias	36	84	143		29.5	58	107		31	54.5	98	
Fast food restaurants	16	28	50		14	23	35		19	26	42	

¹ Resources are counts per 3-kilometer network around participant residence unless otherwise noted.

² Road network measures are within a 1-kilometer Euclidian buffer around participant residence.

³ Beta index is the ratio of links to nodes in a network, where links are street segments and nodes include intersections and street endings (e.g., cul de sacs). A higher beta index indicates greater street connectivity.

⁴ Intersection density is the number of 3- and 4-way intersections per buffer area (i.e., nodes not including cul de sacs/dead-ends). A higher intersection density reflects greater street connectivity.

⁵ Parks are the count within a 3-kilometer Euclidian buffer around participant residence.

Table 2Distribution of individual- and community-level variables according to study year and neighborhood clusters¹.

		Lower population density (<1,750 people per sq km)			Higher population density (≥ 1,750 people per sq km)		
		Low obesogenicity, moderate development	Moderate obesogenicity, high development	High obesogenicity, low development	Low obesogenicity, high development	Moderate obesogenicity, moderate development	High obesogenicity, high development
Year 7	n	443	161	831	821	939	659
	Age (y)	32.1 (3.5)	31.9 (3.8)	32.0 (3.5)	32.3 (3.4)	32.2 (3.7)	31.5 (3.9)
	White (%)	67.9	13.7	60.6	64.8	56	14.3
	Female (%)	50.6	50.3	52.2	54.8	54.2	57.1
	Education (yr)	15.0 (2.4)	14.0 (1.9)	14.6 (2.5)	15.3 (2.6)	14.3 (2.5)	13.5 (2.0)
Community-level	Population density (people per sq km) ²	1,230 (354)	1,224 (342)	666 (424)	5,305 (2,374)	3,194 (1,469)	4,961 (2,047)
	% white, non-Hispanic ³	0.79 (0.23)	0.25 (0.28)	0.72 (0.32)	0.63 (0.29)	0.58 (0.28)	0.15 (0.19)
	% education high school ³	0.15 (0.10)	0.37 (0.11)	0.20 (0.14)	0.17 (0.16)	0.20 (0.11)	0.35 (0.12)
	% income < 150% federal poverty level ³	0.17 (0.14)	0.43 (0.17)	0.18 (0.16)	0.27 (0.21)	0.23 (0.16)	0.38 (0.13)
Year 10	n	808	284	894	580	766	494
	Age (y)	35.2 (3.5)	34.8 (3.8)	35.1 (3.5)	35.0 (3.6)	35.1 (3.7)	34.7 (3.8)
	White (%)	67.1	16.9	64.2	52.4	55.9	14.4
	Female (%)	51.7	57	54.6	52.9	54.3	60.9
	Education (yr)	15.1 (2.7)	13.6 (2.1)	15 (2.5)	14.9 (2.6)	14.6 (2.6)	13.4 (2.1)
Community-level	Population density (people per sq km) ²	1,109 (389)	1,135 (409)	453 (359)	5,007 (2,895)	2,756 (926)	4,373 (1,901)
	% white, non-Hispanic ³	0.82 (0.20)	0.32 (0.32)	0.81 (0.24)	0.57 (0.29)	0.65 (0.28)	0.23 (0.26)
	% education high school ³	0.13 (0.10)	0.35 (0.11)	0.18 (0.13)	0.20 (0.15)	0.18 (0.10)	0.34 (0.12)
	% income < 150% federal poverty level ³	0.13 (0.13)	0.38 (0.17)	0.14 (0.13)	0.28 (0.19)	0.19 (0.14)	0.36 (0.14)
Year 15	N	851	292	829	633	531	458
	Age (y)	40.4 (3.5)	40.0 (3.7)	40.1 (3.5)	40.2 (3.6)	40.0 (3.7)	39.7 (3.9)

		Lower population density (<1,750 people per sq km)				Higher population density (1,750 people per sq km)			
		Low obesogenicity, moderate development	Moderate obesogenicity, high development	High obesogenicity, low development	Low obesogenicity, high development	Moderate obesogenicity, moderate development	High obesogenicity, high development		
	White (%)	69.8	14.4	63.4	56.9	57.1	17		
	Female (%)	51.7	59.9	54.5	54.5	56.3	59.8		
	Education (yr)	15.4 (2.5)	13.8 (2.1)	15.1 (2.5)	15.2 (2.5)	15.0 (2.5)	13.7 (2.3)		
Community-level	Population density (people per sq km) ²	1,097 (384)	1,077 (382)	470 (359)	4,710 (2,800)	2,819 (1,514)	4,572 (2,163)		
	% white, non-Hispanic ³	0.74 (0.22)	0.19 (0.24)	0.73 (0.28)	0.54 (0.25)	0.58 (0.28)	0.16 (0.21)		
	% education high school ³	0.10 (0.08)	0.28 (0.11)	0.14 (0.10)	0.15 (0.11)	0.16 (0.11)	0.31 (0.12)		
	% income<150% federal poverty level ³	0.13 (0.11)	0.40 (0.15)	0.14 (0.12)	0.24 (0.15)	0.16 (0.11)	0.35 (0.13)		
Year 20	N	886	280	912	600	438	390		
	Age (y)	45.3 (3.5)	45.1 (3.7)	44.9 (3.6)	45.1 (3.6)	45.2 (3.6)	44.9 (3.8)		
	White (%)	66.9	14.3	64.8	54.3	61.4	15.1		
	Female (%)	53.3	58.9	55.6	56.0	57.3	63.3		
	Education (yr)	15.5 (2.6)	13.8 (2.0)	15.2 (2.5)	15.2 (2.6)	15.2 (2.6)	13.7 (2.3)		
Community-level	Population density (people per sq km) ²	1,064 (407)	1,061 (394)	399 (339)	4,563 (2,832)	2,643 (987)	4,538 (2,230)		
	% white, non-Hispanic ³	0.76 (0.02)	0.24 (0.29)	0.78 (0.24)	0.52 (0.25)	0.60 (0.27)	0.16 (0.22)		
	% education high school ³	0.10 (0.08)	0.27 (0.11)	0.13 (0.09)	0.16 (0.13)	0.15 (0.10)	0.31 (0.11)		
	% income<150% federal poverty level ³	0.12 (0.11)	0.37 (0.16)	0.13 (0.11)	0.24 (0.16)	0.14 (0.10)	0.35 (0.13)		

¹ Neighborhood clusters are ordered from low to high obesogenicity within population density strata.

² Population density of 3-km buffer around participant home address, calculated as the area-weighted densities of included census tracts in 3-km coverage.

³ Census tract level indicators.

Table 3

Multivariable-adjusted¹ regression coefficients² for associations between neighborhood clusters³ and diet, physical activity, and BMI.

		Low obesogenicity, moderate development	Moderate obesogenicity, high development	High obesogenicity, low development	Low obesogenicity, high development	Moderate obesogenicity, moderate development	High obesogenicity, high development
<i>A priori</i> diet quality score ⁴ Mean(SD): 68.4(12.6)	Model 1	ref	-7.01 (-8.24, -5.79)	-2.2 (-3.02, -1.39)	ref	-2.02 (-2.88, -1.16)	-6.23 (-7.2, -5.27)
	Model 2	ref	-2.04 (-3.26, -0.82)	-0.91 (-1.69, -0.14)	ref	-1.19 (-1.99, -0.38)	-1.86 (-2.81, -0.91)
	Model 3	ref	-1.23 (-2.51, 0.05)	-0.97 (-1.90, -0.05)	ref	-0.88 (-1.73, -0.03)	-1.19 (-2.18, -0.20)
Fast food (freq/wk) Mean(SD): 1.76 (2.35)	Model 1	ref	0.23 (0.13, 0.32)	0.12 (0.05, 0.18)	ref	0.10 (0.02, 0.18)	0.26 (0.17, 0.35)
	Model 2	ref	-0.03 (-0.12, 0.07)	0.03 (-0.03, 0.10)	ref	0.10 (0.02, 0.18)	0.08 (-0.01, 0.17)
	Model 3	ref	-0.03 (-0.13, 0.07)	0.07 (0, 0.15)	ref	0.06 (-0.02, 0.14)	0.02 (-0.07, 0.11)
Physical activity (total units) ⁵ Mean(SD): 339 (277)	Model 1	ref	-47.08 (-66.1, -28.06)	-15.69 (-28.27, -3.11)	ref	-10.13 (-23.94, 3.67)	-25.98 (-42.10, -9.85)
	Model 2	ref	-14.37 (-34.13, 5.38)	-3.20 (-15.77, 9.37)	ref	-6.70 (-20.37, 6.96)	-5.05 (-21.49, 11.38)
	Model 3	ref	-7.77 (-28.32, 12.78)	-7.19 (-21.91, 7.54)	ref	-6.09 (-20.51, 8.33)	-1.37 (-18.34, 15.60)
Walking (freq/wk) Percentage any: 73.1 Mean(SD) among walkers: 12.1 (12.9)	Model 1	ref	-0.54 (-0.77, -0.31)	-0.13 (-0.29, 0.03)	ref	-0.14 (-0.33, 0.04)	-0.67 (-0.87, -0.48)
	Model 2	ref	0.15 (-0.09, 0.39)	0.02 (-0.14, 0.19)	ref	-0.16 (-0.34, 0.02)	-0.24 (-0.44, -0.03)
	Model 3	ref	0.14 (-0.12, 0.39)	0.03 (-0.16, 0.23)	ref	0.03 (-0.17, 0.22)	-0.12 (-0.33, 0.09)
Running (freq/wk) Percentage any: 32.3 Mean(SD) among runners: 5.0 (10.1)	Model 1	ref	-0.58 (-0.86, -0.31)	-0.17 (-0.34, 0.01)	ref	-0.08 (-0.27, 0.11)	-0.30 (-0.51, -0.08)
	Model 2	ref	-0.36 (-0.64, -0.07)	-0.06 (-0.23, 0.12)	ref	-0.03 (-0.21, 0.16)	-0.10 (-0.33, 0.13)
	Model 3	ref	-0.13 (-0.43, 0.17)	-0.06 (-0.27, 0.15)	ref	-0.01 (-0.21, 0.19)	-0.04 (-0.27, 0.20)
Biking (freq/wk) Percentage any: 38.7 Mean(SD) among bikers: 4.8 (9.0)	Model 1	ref	-0.72 (-0.95, -0.48)	-0.34 (-0.49, -0.19)	ref	0.06 (-0.11, 0.22)	-0.59 (-0.77, -0.40)
	Model 2	ref	-0.05 (-0.31, 0.20)	-0.11 (-0.26, 0.05)	ref	0.09 (-0.07, 0.25)	-0.21 (-0.41, -0.02)
	Model 3	ref	0.15 (-0.12, 0.41)	-0.08 (-0.27, 0.10)	ref	0.10 (-0.07, 0.27)	-0.13 (-0.33, 0.07)
Ln-BMI (kg/m ²) Mean(SD): 3.31 (0.22)	Model 1	ref	0.016 (0.008, 0.024)	0.002 (-0.003, 0.008)	ref	-0.001 (-0.007, 0.006)	0.002 (-0.006, 0.009)
	Model 2	ref	0.01 (0.001, 0.018)	0.001 (-0.004, 0.007)	ref	-0.001 (-0.008, 0.005)	-0.006 (-0.014, 0.001)
	Model 3	ref	0.01 (0.001, 0.019)	0.002 (-0.005, 0.008)	ref	-0.002 (-0.009, 0.004)	-0.008 (-0.016, 0)
Ln-HOMA-IR Mean(SD): 0.99 (0.61)	Model 1	ref	0.042 (0.001, 0.083)	0.006 (-0.021, 0.034)	ref	0.048 (0.017, 0.078)	0.061 (0.025, 0.097)
	Model 2	ref	-0.025 (-0.068, 0.018)	-0.008 (-0.036, 0.02)	ref	0.038 (0.008, 0.069)	0.009 (-0.028, 0.046)
	Model 3	ref	-0.038 (-0.083, 0.006)	-0.013 (-0.045, 0.019)	ref	0.034 (0.002, 0.067)	-0.007 (-0.045, 0.032)

¹ Model 1: adjusted for age and study year; Model 2: additionally adjusted for race, gender, study center, educational attainment; Model 3: additionally adjusted for census tract-level education (% of tract < HS, % of tract > college) and income (median family income, % of tract < 150% federal poverty level).

² Coefficients from linear regression models for *a priori* diet quality score, total PA units, and BMI; negative binomial regression models for fast food consumption; and two-part models for walking, running, and biking frequency. Two-part models comprised a binomial model for any engagement (e.g., any walking), followed by a linear model for amount (weekly frequency) among those who reported engaging in the activity (e.g., weekly frequency of walking among those who reported any walking).

³ Neighborhood clusters are ordered from low to high obesogenicity within population density strata.

⁴ The *a priori* diet quality score is a continuous measure of foods consumed. Foods are scored positively or negatively based on hypothesized relations to health. Higher scores indicate higher diet quality.

⁵ Physical activity units are a continuous measure calculated from the frequency and intensity of engaging in 13 specific activities. Higher scores indicate more physical activity.