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Patterns of food and physical activity environments related to children's food and activity behaviors: a latent class analysis

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Abstract

Relationships between food and physical activity (PA) environments and children's related behaviors are complex.

Latent class analyses derived patterns from proximity to healthy and unhealthy food outlets, PA facilities and parks, and counts of residential dwellings and intersections. Regression analyses examined whether derived classes were related to food consumption, PA, and overweight among 404 low-income children.

Compared to children living in Low PA-Low Food environments, children in High Intersection & Parks-Moderate Density & Food, and High Density-Low Parks-High Food environments, had significantly greater sugar-sweetened beverage consumption (ps<.01) and overweight/obesity (ps<.001). Children in the High Density-Low Parks-High Food environments were more likely to walk to destinations (p=.01)

Recognizing and leveraging beneficial aspects of neighborhood patterns may be more effective at positively influencing children's eating and PA behaviors compared to isolating individual aspects of the built environment.

Keywords

environment; ecological; nutrition; exercise; latent class analysis; finite mixture modeling

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Introduction

The majority of US children neither consume diets considered healthy according to the standards set forth in the 2015–2020 Dietary Guidelines for Americans (US Department of Agriculture and US Department of Health and Human Services 2015), nor participate in the recommended amount of physical activity (PA) per the 2008 Physical Activity Guidelines for Americans (US Department of Health and Human Services 2008). Fewer than 30% of children meet or exceed the recommended intake of fruit, about 7% consume enough vegetables, and less than 1% meet whole grain intake recommendations (Kirkpatrick et al. 2012). Only 8% of adolescents and fewer than half of 6- to 11-year-old children engage in the recommended 60 or more minutes of daily moderate or vigorous activity (Troiano et al. 2008, US Department of Health and Human Services 2008).

The social ecological model of health behavior posits that dietary and PA behaviors do not occur in a vacuum, and that attempting to explain or predict behavior at the individual level only is insufficient (Glanz, Mullis 1988). Rather, it is important to recognize that an individual can simultaneously act on the environment and be influenced by multiple elements of the environment (Bandura 1977); relationships among individual characteristics and those of the physical and sociocultural environments must be taken into account.

Food and PA environments have been examined for their roles in nutrition and activity behaviors, respectively. While availability (i.e., proximity, density, and presence) of various types of food outlets have been associated with children's food intake, these relationships appear inconsistent due in part to differences in how availability has been conceptualized and measured (Lytle 2009). For example, in a study of 9–10-year-old children, *proximity* to a supermarket was not associated with increased fruit and vegetable intake, but a higher *density* of supermarkets (i.e., number per km^2) near children's homes was associated with higher vegetable intake (Skidmore et al. 2010). Similarly, low- and middle-income children participating in the 2006 Health Behavior in School Aged Children Study had lower odds of consuming fruits and vegetables when they attended schools in areas with a high density of fast food outlets and low density of supermarkets (Svastisalee, Holstein & Due 2012). Sugar-sweetened beverage (SSB) intake has been associated with the presence of any convenience stores or grocery stores within 1600 meters, and restaurants within 800 and 1600 meters, of adolescents' homes (Laska et al. 2010). Others, however, have observed no associations between food outlet availability and food intake (An, Sturm 2012).

The PA environment includes not only public and private recreation environments such as parks or gyms for leisure activity, but also urban form aspects, such as higher street connectivity and residential densities, that facilitate active transportation. As observed with relationships between food environments and dietary behaviors, associations between PA environments and PA behaviors have been mixed for children across different age groups (Ding et al. 2011). For example, among 3–12 year-olds, street connectivity (e.g., higher intersection density, fewer cul-de-sacs) has been found to be positively (Roemmich et al. 2007, Frank et al. 2007), negatively (Carver, Timperio & Crawford 2008), and not (Larsen et al. 2009, Kerr et al. 2007, Braza, Shoemaker & Seeley 2004) related to PA outcomes. However, residential density has been consistently associated with increased walking for transportation (Sallis et al. 2016, Larsen et al. 2009, Frank et al. 2007) among adults and children (Ding et al. 2011). Associations between park proximity and density and children's measured activity have been mixed as well (Bancroft et al. 2015).

Inconsistent findings observed for environmental measures may be attributed to methodological differences among studies, as well as differences in settings and subjects (Lytle 2009, Brownson et al. 2009). Most studies have been designed to identify, via multivariable regression analyses, the unique effect of each environmental feature after adjusting for those of others. These analyses, however, have not accounted for the potential impact of the *combined* presence or absence of a variety of environmental features, as patterns of features in fact occur like mosaics in communities. Because environmental factors are complex and interact in multiple ways, it is critical to consider multiple factors when attempting to predict individual-level behaviors (Sallis, Owen & Fisher 2008) rather than attempting to isolate the potential contribution of each environmental characteristic (Kurka et al. 2015, Adams et al. 2013, Wall et al. 2012, Norman et al. 2010).

Several data driven approaches are possible for examining combinations of factors. Clustering methods, in contrast to a multiple regression modeling approach, can reduce model complexity while still retaining information from several environmental indicators, but some methods have important limitations. Though traditional cluster analysis methods (e.g., k-means clustering) can identify groups of similar observations, they place constraints on indicator scaling and do not afford straightforward statistical comparisons among models. Supervised machine learning methods (e.g., support vector machines) can identify groups of similar observations while allowing for statistical comparisons, but these methods rely on first "training" a clustering model using sets of observations that have *a priori* known class memberships. Latent class analysis (LCA) is an empirical approach for identifying distinct *patterns* of separate categorically-scaled environmental features within unknown class memberships, in which each identified class represents a distinctive pattern of indicator categories (e.g., presence vs. absence of each environmental feature). Further, LCA allows for statistical comparisons of solutions that differ in the numbers of classes extracted. Once these patterns of environmental features have been identified, they can then be related to the individual-level behaviors of interest (Meyer et al. 2015).

The purpose of this study was to examine the presence of patterns (latent classes) of objectively-measured built environment features, such as PA facilities, public parks, intersections, residential dwellings, and healthy and unhealthy food outlets across low-income New Jersey communities. Associations between derived latent classes and reported dietary and PA behaviors and weight outcomes among children were then analyzed. We hypothesized (a) that LCA would identify at least one pattern characterized by both high access to unhealthy food options and low access to PA opportunities, and (b) that this pattern would be associated with poorer dietary and PA outcomes relative to other patterns.

Methods

Study Population

The data for this study were collected from June 2009 through March 2010 from a random-digit-dial sample of 1408 households with at least one child in the age range of 3 to 18 years, and with landline telephones. Households were located in Camden, Newark, New Brunswick, and Trenton, New Jersey. Using standard calculations (The American Association for Public Opinion Research 2009) the sample of 1408 represented a 49% response rate, similar to the Center for Disease Control and Prevention's (CDC) New Jersey Behavioral Risk Factor Surveillance System (BRFSS) 2010 response rate of 50.2%. One child from each household was randomly selected as the index child, and survey questions focused on him/her. The sample was representative of 3–18-year-old children in each of the four cities included in the study, as compared to the 2000 Census, with similar racial/ethnic, age, and gender group proportions represented (US Census Bureau 2016). The respondent was the adult who made most of the food-shopping decisions for the household (referred to as parent). A multi-call design was used to conduct telephone interviews, which were conducted in either Spanish or English and took 36 minutes to complete. Participants were offered a $10 incentive upon completion. At the conclusion of the survey parents were asked to participate in a follow-up study in which they weighed and measured themselves and their children using instructions based on CDC guidelines (Centers for Disease Control and Prevention 2014) and a tape measure mailed to their homes along with a reporting worksheet. Parent-measured heights and weights of children have been reported to highly correlate with professionally measured values (Carnell, Wardle 2008) and are more accurate than are parent-reported estimates (Huybrechts et al. 2011). An additional $10 incentive was offered for completion of this task. Approximately 40% (n = 485) of the surveyed households who provided their mailing addresses returned completed worksheets with measured heights and weights for the index child.

The Institutional Review Boards of Rutgers University and Arizona State University approved study protocols. Participants provided informed consent before the start of the study.

Parent- and child-level characteristics

Demographic variables measuring parent and index child characteristics were assessed by asking parents, "Is the child a male or female?"; "What is the child's age?"; "Is the child of Spanish, Hispanic, or Latino origin or descent?"; "What is the child's race?" (race/ethnicity categorized into non-Hispanic white, non-Hispanic black, Hispanic); "Was the child born outside of the United States, Puerto Rico, or other US territories?"; "What is the highest grade or level of school the child's mother has completed?" (categorized into high school or less, some college, bachelors or higher); "During 2008, what was your family's total income from all sources, before taxes and other deductions? (including job wages, public assistance, social security, child support, and any other sources of income)?" (converted to a ratio of the US federal poverty level [FPL]).

Outcome variables

Survey questions also assessed the index child's food consumption and PA behaviors. Questions were derived from validated surveys, as cited below.

Food behavior—Parents were asked, "How often over the past month (i.e., times per month, week, or day) did the child eat 1) a green leafy or lettuce salad, with or without other vegetables; 2) potatoes (excluding French fries or other fried potatoes) such as baked, boiled, mashed, or potato salad; 3) cooked or canned dried beans, such as refried beans, baked beans, bean soup, tofu, or lentils; 4) other vegetables such as tomatoes, green beans, carrots, corn, cooked greens, sweet potatoes, broccoli, or any other kinds of vegetables?" (Centers for Disease Control and Prevention 2008, Centers for Disease Control and Prevention 2016b, Centers for Disease Control and Prevention 2016a, UCLA Center for Health Policy Research 2012). The frequency of consumption of these four types of vegetables was combined to estimate the overall frequency of vegetable consumption used in the analysis. To estimate children's fruit consumption, parents were asked, "Not counting juice, how often (times per month, week, or day) did the child eat fresh, frozen, or canned fruit?" (Centers for Disease Control and Prevention 2008, Centers for Disease Control and Prevention 2016b, Centers for Disease Control and Prevention 2016a). The overall frequency of consumption of fruits and vegetables were combined and used in the analysis (referred to as FV). Fast food frequency consumption was assessed by asking parents, "How often over the past month (times per month, week, or day) did the child eat at a fast food restaurant, deli, pizza, burger, taco, or chicken place where you pay before you eat?" (Nelson, Lytle 2009, Murphy et al. 2001, UCLA Center for Health Policy Research 2012). To assess the child's SSB consumption frequency, parents were asked, "How often over the past month (times per month, week, or day) did the child drink 1) regular carbonated soda or soft drinks that are sweetened, such as Coke [The Coca-Cola Company], Pepsi [PepsiCo, Inc.], or 7-Up [Dr. Pepper Snapple Group] (not including diet drinks) and 2) fruit-flavored drinks (not including 100% fruit juice), such as lemonade, Sunny Delight [Sunny Delight Beverages Company], Kool-Aid [Kraft Foods], Gatorade [PepsiCo, Inc.], or sweet iced tea?" (Nelson, Lytle 2009, Centers for Disease Control and Prevention 2008, Centers for Disease Control and Prevention 2016b, UCLA Center for Health Policy Research 2012). The frequency of consumption of these two types of beverages was combined to estimate the overall SSB consumption frequency used in the analysis. Consumption frequencies of salty snacks and sweets were assessed by asking parents, "How often in the past month (times per month, week, or day) did the child eat salty snacks like chips, Doritos, and Nachos" and "sweet items like cookies, cakes, candy, or pies?" (Centers for Disease Control and Prevention 2008, UCLA Center for Health Policy Research 2012), respectively. Food behavior variables were converted to times per day, with the exception of fast food consumption which was converted to times per week.

Physical activity behavior—To assess PA behavior, parents were asked, 1) "On how many days in the past week did the child spend 60 minutes in physical activity that increased his/her heart rate and made him/her breathe hard?" (Centers for Disease Control and Prevention 2016b, UCLA Center for Health Policy Research 2012, Prochaska, Sallis & Long 2001, Kerr et al. 2017, The IPAQ group 2002); 2) "During the school year, how many days during a typical week does the child walk, bicycle, or skateboard to or from school (do not include motor scooters)" (UCLA Center for Health Policy Research 2012, Kerr et al. 2017); 3) "How often does the child walk to stores, libraries, or recreational facilities in your neighborhood? (often, sometimes, rarely, never, no such places to walk)" (Kerr et al. 2017, The IPAQ group 2002). Significant correlations have been found between parent-report and child-report of food and PA behaviors in both young ($r = 0.57, 0.88$) (Bennett et al. 2009) and 10 to 17 year-old children (Mean: $r = 0.50$; range: $r = 0.23, 0.64$) (Lamb et al. 2007). In the current study, PA variables were dichotomized based on observed bimodal distributions: 60 minutes of daily activity on seven days per week versus fewer than seven days; ever walked or biked to school versus never; walked to destinations often versus sometimes, rarely, or never.

Weight status—Children were classified as either normal weight or overweight/obese based on the age- and sex-specific percentile of the child's BMI, calculated with the measured height and weight provided on the parents' worksheet and scored with the 2000 CDC Growth Charts (Centers for Disease Control and Prevention 2009). Children with a BMI below the 85th percentile were considered normal weight. Those children at or above the 85th percentile were classified as overweight/obese.

Neighborhood characteristics

Lists of food and PA outlets within a one-mile radius around city boundaries were obtained from commercial and publicly available sources (InfoUSA and Trade Dimensions) and were de-duplicated. Locations of participants' homes and of food outlets and PA venues were geocoded using street addresses in ArcGIS 10.1 (ESRI, Redlands, CA). Using methodology developed by Ohri-Vachaspati et al. (2011), food outlets were categorized as either supermarkets (large national or local chain; sales volume over $2 million), small grocery stores (sales volume less than $2 million; sell at least 3 of the following 4 food items: 5 or more different kinds of fresh fruit, 5 or more different kinds of fresh vegetables, fresh or frozen meat, skim or lowfat milk), convenience stores (small store that sells fewer than 3 of the 4 food previously-named food items), or limited service restaurants (customers pay before receiving food, e.g., national fast-food chain). Public and private PA facilities (with and without fees) and public parks larger than one acre were identified using data from county and city departments, web-based searches, Yellow Pages, and commercial data sources (InfoUSA). Lists were de-duplicated, and parks and facilities were classified based on methodology proposed by Abercrombie et al. (2008). Lists of residential dwellings were obtained in 2011 from the US American Community Survey (US Census Bureau 2016), and road network data (for enumerating street intersections) were obtained from the New Jersey Geographic Network (New Jersey Geographic Information Network 2014). These data were used to form eight dichotomous indicators of a participant's local food and PA environments.

Findings from previous research examining distributions of the current built environment data show that distances over a quarter mile from the participant's home (e.g., half mile or one mile) yield very low between-household (i.e., between-participant) variability in PA and food environment characteristics (Ohri-Vachaspati et al. 2013, Ohri-Vachaspati et al. 2015).

Accordingly, a quarter-mile roadway network buffer (defined using GIS methods) around each home was selected to characterize the local food and PA environments. The presence (or absence) of each of the four types of food outlets (supermarket, small grocery store, convenience store, fast food restaurant) and each of two types of PA venues (park, PA facility) and the counts of residential dwellings and street intersections with 3 or more legs within each buffer were derived. Counts of residential dwellings and street intersections were categorized with respect to the sample median on each feature (i.e., above vs. below median number of residential dwellings; above vs. below median count of intersections).

Block group characteristics

Home locations were linked with their corresponding Census block group's demographic characteristics, including race/ethnicity (percentage of non-Hispanic black and Hispanic), education level (percentage of some college and bachelor's or higher), median household income, and crime data. Block groups were characterized by the subgroup that composed at least a 51% proportion of a given characteristic. For example, block groups in which 51% or more of residents had only a high school education or less were defined as 'majority high school or less.' These definitions helped group neighborhoods based on their predominant characteristics rather than incremental differences in proportions. Block group characteristics were obtained from pooled 2005–2009 American Community Survey data (US Census Bureau 2016). Crime index (CrimeRisk) data were purchased from Applied Geographic Solutions (AGS). CrimeRisk provides relative crime rate for each census block group in the country, based on an analysis of the FBI's Uniform Crime Report (UCR) data over an extended period of time. The national average for CrimeRisk is indexed at 100, and a block group's score of 50 or 200 is half or twice the national average. For the current data, AGS used UCR's from 1998–2006 and over 65 census socioeconomic characteristics to develop Census block-group level estimates (Applied Geographic Solutions 2008). Consistent with the reporting procedures used in the UCR, aggregate indexes are available for personal and property crimes individually, as well as a total index. Total CrimeRisk index scores were used to adjust for neighborhood crime.

Latent class analysis

After excluding index children with incomplete height and weight data (n=45), 440 were included in analyses. Latent class analyses (LCA) were performed on the eight dichotomous neighborhood characteristics (supermarkets, small grocery stores, convenience stores, fast food restaurants, residential dwellings, intersections, parks, PA facilities) using Mplus v7.11 (Los Angeles, CA). Table 1 shows the proportions of the dichotomous neighborhood characteristics prior to the LCA (a priori sample probabilities). LCA seeks to classify participants based on patterns of categorical indicators. The procedure maximizes between-class variance and minimizes within-class variance resulting in participants being classified into mutually exclusive sub-groups (i.e., classes) of an unobserved latent categorical variable based on the relative similarity of their patterns of indicator values. Solutions for the number of latent classes were examined sequentially starting with a 2-class model and progressing until resultant models were uninterpretable or model fit criteria (AIC, BIC, log-likelihood) showed no substantial improvement. Once the optimal model was determined, participants were assigned to a single class based on the highest estimated probability of class membership. Classes were characterized by the probability of particular indicators being greater than the median cut-point (residential dwellings, intersections) or present (parks, PA facilities, supermarkets, small grocery stores, convenience stores, fast-food restaurants) within the quarter-mile buffer. Participants were assigned to the class for which they had the highest probability of membership. Table 2 shows the average maximum probability of membership for each class.

Regression analysis for associations between classes and food/PA behaviors and weight outcomes

Regression analyses tested for associations between the derived classes and eating and PA behaviors, and weight outcomes after adjusting for child, parent, and block group level factors using PROC GENMOD SAS 9.4 (SAS Institute, Cary, NC). Index children with biologically implausible BMI z-scores (n=36) (Centers for Disease Control and Prevention 2017), as well as those missing demographic or outcome variables were excluded. All food consumption measures were frequency-based count variables (e.g., number per day or week) and showed positive skew. Accordingly, these were modeled specifying a negative binomial distribution with log link function. For the PA and weight variables, a binomial distribution with logit link function (i.e., logistic regression) specification was used. In all models, standard errors were adjusted for clustering (non-independence) at the city level. Three models were run for each outcome variable. In Model 1, LCA class membership (represented by two dummy variables) was the only predictor. In Model 2, variables representing parent- and child-level factors were added to Model 1. Model 3 comprised predictors from Model 2 plus the block group characteristic variables.

We conducted a sensitivity analysis comparing the fit of a model using latent class membership to a model using individual environmental features as predictors. Relative model fit was evaluated by comparing model quasilikelihood under the independence model criterion (QIC) values (analogous to using Akaike information criterion, or AIC, values for comparing model fit using likelihood-based methods). A lower QIC value indicates superior model fit, after accounting for model complexity (i.e., number of model parameters).

Under Model 3 (i.e., adjusting for child- and parent-level variables and block group characteristics), the model using class membership fit better than the model using individual neighborhood characteristics as predictors for every outcome except SSB consumption and walking to destinations, where differences between QIC values were minimal (SSB: Latent Class QIC=533.98, individual features QIC=532.52; walk to destinations: Latent Class QIC=458.52, individual features QIC=456.92).

Results

Latent class analysis

LCA of 2-, 3-, and 4-class solutions were explored. A 3-class model (AIC=3644.98, BIC=3751.24, log-likelihood=−1796.49) was retained due to robust interpretability and substantial improvement in fit statistics compared to the 2-class model (AIC=3684.81, BIC=3754.29, log-likelihood=−1825.41) and no substantial improvement in fit statistics in the 4-class model (AIC=3639.64, BIC=3782.68, log-likelihood=−1784.82).

Figure 1 depicts the identified classes and their respective conditional probabilities for the presence of parks, PA facilities, supermarkets, small grocery stores, convenience stores, and fast-food restaurants, and of having above-median residential dwellings and intersections. The a priori sample proportions were used as a reference point in Figure 1 and are indicated by a horizontal black line for each neighborhood characteristic. The first class (n=72, 17% of sample), labeled "Low PA-Low Food," was characterized by having the lowest probability for above-median residential dwellings and intersections, as well as the lowest probability for the presence of a PA facility, supermarket, small grocery store, convenience store, and fast-food restaurant. Low PA-Low Food was also characterized by having a high probability of the presence of a large park. The second identified class (n=148, 34% of sample), labeled "High Intersection & Parks-Moderate Density & Food," was characterized by having the highest probability for above-median intersections and for the presence of large parks, and low probabilities of having a PA facility, a supermarket, and a small grocery store. The third class (n=220, 49% of sample), labeled "High Density-Low Parks-High Food" was characterized by having the highest probability of above-median residential dwellings and the presence of PA facilities, supermarkets, small grocery stores, convenience stores, and fast-food restaurants. The third class also included the lowest probability for large park presence.

Child and parent characteristics

The average age of children in the overall sample was 10.9±4.4 years. About half (49%) of the children were non-Hispanic black, and 7% were non-Hispanic white. The majority of parents (61%) had only a high school education or less, and about 8% were foreign-born. Seventy-one percent of children in the Low PA-Low Food class were male, significantly more than in the other two classes. The High Intersection & Parks-Moderate Density & Food class had the fewest parents with at least a bachelor's degree or higher (7%). Parents in the Low PA-Low Food class had significantly higher incomes (376% of FPL) compared to parents in the other two classes (High Intersection & Parks-Moderate Density & Food: 221% of FPL; More Dense-High Food- Low PA: 190% of FPL) (Table 3).

Block group characteristics

In the overall sample, participants lived in block groups composed primarily of non-Hispanic black and Hispanic residents. The majority of residents in 31% of block groups had attended some college or had earned a bachelor's degree or higher. The average block group median income was approximately $36,900±16,200, and the average total crime index for the sample was 305.60, three times the national average of 100.

As was the case with the full sample, block groups in each latent class were also composed primarily of non-Hispanic blacks and Hispanics. Majority education levels differed significantly across the three classes, with the High Density-Low Parks-High Food class having significantly fewer block groups in which the majority of residents had attained a bachelor's degree or higher (High Density-Low Parks-High Food: 7%; Low PA-Low Food:

25%; High Density-Low Parks-High Food: 16%). Median household income showed similar patterns to those observed for education. Among the three classes, total crime was significantly higher in the High Intersection & Parks-Moderate Density & Food class (349.50) compared to the other two classes (Low PA-Low Food: 280.84; High Density-Low Parks-High Food: 283.85) (Table 3).

Unadjusted outcome variables are summarized by LCA class in Table 4. Neither healthy nor unhealthy food intake differed across classes. Participants reported walking-to-destinations differed significantly across classes, with 31%, 30%, and 18% of participants in High Intersection & Parks-Moderate Density & Food, High Density-Low Parks-High Food, and Low PA-Low Food neighborhoods, respectively, reporting walking to destinations often. Fewer overweight/obese children lived in the Low PA-Low Food neighborhood than in the other two neighborhoods (Low PA-Low Food: 20%; High Intersection & Parks-Moderate Density & Food: 41%; High Density-Low Parks-High Food: 38%).

Prediction of Behaviors

Healthy and unhealthy food—Table 5 summarizes results of unadjusted and adjusted negative binomial regression models predicting consumption of vegetables. The only significant difference was observed in Model 2 (adjusting for child/parent level variables), in which children in the High Intersection & Parks-Moderate Density & Food class consumed vegetables 6% less often compared to those in the Low PA-Low Food class (PR = 0.94, 95% CI 0.92–0.96, $p<.001$). However, this association was no longer significant after adjusting for block group characteristics in Model 3.

The results of unadjusted and adjusted negative binomial regression models predicting unhealthy food outcomes are also summarized in Table 5. The patterns for unhealthy food intake showed a number of significant differences across LCA classes. In Model 1 for all outcomes except fast food, significant differences existed across classes. Children in the High Intersection & Parks-Moderate Density & Food class consumed 36% more salty snacks (PR = 1.36, 95% CI 1.13–1.64, $p<.001$) than did children in the Low PA-Low Food class. This association, however, was not significant in Models 2 and 3, when adjusting for child/parent-level characteristics, and block group characteristics. SSB intake was significantly higher in both High Intersection & Parks-Moderate Density & Food (PR = 1.33, 95% CI 1.08–1.64, $p=.008$) and High Density-Low Parks-High Food (PR = 1.27, 95% CI 1.09–1.47, $p=.002$) classes compared to the Low PA-Low Food class in Model 3 after adjusting for all covariates. There was also a greater probability for consumption of sweets in the High Intersection & Parks-Moderate Density & Food (PR = 1.41, 95% CI 1.07–1.88, $p=.016$) and High Density-Low Parks-High Food (PR = 1.29, 95% CI 1.01–1.65, $p=.038$) classes compared to the Low PA-Low Food class, before adjusting for covariates.

Physical activity—The results of unadjusted and adjusted binomial logistic regression models predicting PA outcomes are summarized in Table 6. Children in the High Density-Low Parks-High Food class had higher odds of walking or biking to school (OR = 1.63, 95% CI 1.17–2.27, $p=.004$) and to other destinations (OR = 1.98, 95% CI 1.02–3.83, $p=.043$) compared to children in the Low PA-Low Food class, before adjusting for covariates. The associations remained significant for walking to destinations after adjusting for child, parent, and block group characteristics (OR = 1.78, 95% CI 1.15–2.77, p=.010).

Weight status—Unadjusted and adjusted binomial logistic regression models were used to predict weight outcomes among children. Children in the High Intersection & Parks-Moderate Density & Food and High Density-Low Parks-High Food classes had 129% and 148% higher odds, respectively, of being overweight or obese compared to children in the Low PA-Low Food class after adjusting for all covariates. These differences were significant.

Discussion

Much of the existing literature has tried to isolate the effects on eating and PA behaviors of specific types of food (Boone-Heinonen et al. 2011, Cummins, Flint & Matthews 2014, Block et al. 2011) or PA outlets (Ohri-Vachaspati et al. 2013, Evenson et al. 2013), as well as urban form environmental aspects (Ding et al. 2011, Sallis et al. 2016), independent of other environmental factors. A more likely scenario is that patterns of environment characteristics act synergistically to impact behaviors (Nelson et al. 2006). The current study utilized LCA to empirically characterize eight neighborhood features (and 256 possible combinations of features), selected for their combined conceptual influence on overweight and obesity, into three prevalent neighborhood types: High Density-Low Parks-High Food; Low PA-Low Food; or High Intersection & Parks-Moderate Density & Food. Participants living in High Density-Low Parks-High Food neighborhoods had higher probabilities of having all types of food outlets (convenience stores, fast food restaurants, small grocery stores, and supermarkets) within a quarter mile radius of a child's home. The Low PA-Low Food neighborhood had lower probabilities of above-median numbers of residential dwellings and intersections and of having any type of food outlets, but a higher probability of having parks. The High Intersection & Parks-Moderate Density & Food neighborhood had higher probabilities of above median numbers of intersections and of having a park, lower probabilities of having supermarkets and small grocery stores, and higher probabilities of having convenience stores and fast food restaurants, although not as high compared to the High Density-Low Parks-High Food class.

Robust findings were observed in unhealthy compared to healthy eating habits when examining how children's reported food consumption behaviors were associated with class membership. Children living in the High Intersection & Parks-Moderate Density & Food class consumed vegetables 6% fewer times per day compared to children in the Low PA-Low Food class. However, after adjusting for block group characteristics, no differences were observed in vegetable consumption among the three classes. Three of the four unhealthy food behaviors showed significant results in at least one model. Children living in the High Intersection & Parks-Moderate Density & Food neighborhood were 36% more likely to eat salty snacks compared to children in the Low PA-Low Food neighborhood in the unadjusted model. Children in the High Intersection & Parks-Moderate Density & Food and High Density-Low Parks-High Food neighborhoods were 33% and 27%, respectively, more likely compared to children in the Low PA-Low Food neighborhood to drink SSBs in the fully adjusted model. And compared to children in the Low PA-Low Food neighborhood, children in the other two neighborhoods were 41% and 29% more likely to eat sweets in the unadjusted model.

Interestingly, in fully adjusted models, compared to children in the Low PA-Low Food class, children in the High Density-Low Parks-High Food class were 78% more likely to walk to their destinations often, while at the same time having almost two and a half times the prevalence of overweight or obesity. Children living in High Intersection & Parks-Moderate Density & Food neighborhoods were also more than twice as likely to be overweight or obese compared to children in the Low PA-Low Food class. Food and PA environmental factors have previously been found to play a role in children's weight status (DeWeese, Ohri-Vachaspati 2015, Ohri-Vachaspati et al. 2015, Tang et al. 2014, Ohri-Vachaspati et al. 2013). The increased likelihood of overweight and obesity in the neighborhoods with a greater prevalence of food outlets is important to consider when formulating policies to create healthier communities. Policy-makers and community planners must recognize the synergistic role food and activity access play within built environments.

The constellation of food consumption behaviors, PA behaviors, weight outcomes, and food environment observed in this study may be particularly informative with regard to children, who do not have the option of driving themselves to their destinations. A child in an activity friendly neighborhood who regularly walks by retail food stores stocked with cheap, readily available sweet and salty snacks and SSBs is likely to stop in and purchase those items. Borradaile et al. (2009) conducted intercept surveys outside of corner stores located within four blocks of urban K-8 schools. They found that 40% of 4^{th} – 6^{th} grade students shopped there both before and after school each day, purchasing an average of 360 kilocalories per visit, primarily from chips, candy, and sugary beverages.

Our findings suggest that individual food and PA environmental factors interact to form combinations of characteristics as determined by LCA, and the combinations as a whole may exert a greater influence on behaviors than do any of the individual factors of which the combinations are composed. Meyer et al. (2015) also used LCA to examine the combination of both food and PA factors in relation to food and PA behaviors. Their analysis focused on adults, and found an association between lower diet quality and living in a "moderate obesogenicity, moderate development" neighborhood (high street connectivity; moderate PA resources; high percentages of convenience stores, supermarkets, and grocery stores) in low-population areas, and "moderate obesogenicity, moderate development" (moderate levels of all features) and "high obesogenicity, high development" (high street connectivity; many parks, free public PA resources, and convenience stores, high percentage of grocery stores) neighborhoods in higher-population areas.

Given the confluence of walkability and high probability of unhealthy foods nearby within densely populated neighborhoods, healthier outcomes may be achieved by changing the snacks sold at traditionally unhealthy stores (Pinard et al. 2016), as well as reframing what is considered a snack – a mindset change that may only come about through collective efforts of retailers, the public, and public health advocates (Twine 2015). Healthy corner store initiatives continue to launch in neighborhoods across the US as community partners desire an increase in healthy food access (Gittelsohn, Rowan & Gadhoke 2012). These healthy store programs encourage small-store owners to stock and promote more foods with greater nutritional value (The Food Trust, Philadelphia Corner Store Network & Get Healthy Philly 2014); stores participating in these programs have been shown to stock a healthier array of foods (DeWeese et al. 2016). Middle and high school students' weight outcomes have been shown to be inversely associated with the presence within a quarter mile of school of a small grocery store with a selection of healthy options (Tang et al. 2014).

Influences of individual elements may vary depending on the overall environment in which they are located. Wall et al. (2012) used multiple linear regression, exploratory factor analysis, and spatial latent class analysis to explore potential relationships between neighborhood characteristics and adolescent weight outcomes. In regression analysis identifying the association with obesity risk of a single characteristic after adjusting for all others, they found that the presence of a convenience store within 1200 meters of a girl's home was associated with a higher BMI z-score. In latent class analysis, close proximity to a convenience store was part of three different clusters: 1) median density of convenience stores; high socioeconomic status (SES), transit, and parks; 2) high density of convenience stores; nearby supermarket; low SES and safety; 3) high density of convenience stores; low SES and safety. Only one of the clusters was associated with a significantly greater obesity risk among girls.

In a series of studies, Adams et al. (2015, 2013, 2011) and Todd et al. (2016) explored how patterns of environment features including residential density, land use mix, intersection density, bus and rail access, and access to parks and private recreational facilities were associated with PA behaviors and overweight/obesity for all adults and older adults. They consistently found that individuals living in more activity-friendly neighborhoods (i.e., patterns of higher walkability, better access to public transit, parks, and private recreation facilities) walked more for transportation and recreation compared to participants living in activity-unfriendly neighborhoods, and patterns of features explained more variance in outcomes than a 4-component walkability index for objective and self-reported outcomes. Kurka et al. (2015) found similar results in children when investigating associations between out-of-school moderate-to-vigorous PA and latent profiles categorized according to parental perceptions of PA environments. Latent class/profile analysis has provided a more complete picture of environmental influences on PA. Consistent patterns for PA have emerged, with greater objective and self-report PA associated with more activity-friendly environments. However, less prevalent are studies that include both PA and nutrition-related environments. As LCA is utilized more extensively, however, patterns of obesogenic environments may emerge that will inform the greatest groups of influences on specific behaviors.

The Massachusetts Department of Public Health has recognized that preventing and treating chronic diseases requires a tailored approach based on multiple factors at multiple levels. Using 55 variables, including fruit and vegetable consumption, physical activity, land use data, and business establishments, they utilized LCA to divide communities into one of ten classes (Arcaya et al. 2014). Chronic disease interventions will be tailored in the future to specific communities based on class characteristics.

This study contributes to the limited literature using LCA to investigate both the food and PA environments among children (Wall et al. 2012). Another strength is the use of a large sample predominately composed of children from low-income, minority households, which is the population most affected by the built environment (Lovasi et al. 2009). The cross-sectional nature of the data collection is an inherent limitation to examining causal relations. Additionally, while residential self-selection should be considered as potentially attenuating these effects, it is important to note that preferences for neighborhoods and neighborhood food and activity environments themselves slowly change over time. At the time of the survey almost half of sample households had lived in their neighborhoods for 10 or more years. Another 22% had remained in their neighborhoods between 5 and 10 years, minimizing any impact of previous neighborhood self-selection on current outcomes. Further, food consumption and PA behaviors were obtained by parent-report rather than by objective measures. Parent food consumption recall and reports on children's PA have limitations, but also have been shown to be suitable proxies of their children's food consumption and PA levels, respectively (Byers et al. 1993, Lamb et al. 2007, Reinaerts, de Nooijer & de Vries 2007, Sithole, Veugelers 2008). The dietary screener used in the study was developed by the CDC and employed in NHANES 2009–10, and has been validated against 24-hour recalls (Nelson, Lytle 2009, Centers for Disease Control and Prevention 2008, Centers for Disease Control and Prevention 2016a, Murphy et al. 2001, UCLA Center for Health Policy Research 2012). The seven-day PA recall questionnaires used are validated as well and have been used extensively to classify children and adolescents into different activity levels (Prochaska, Sallis & Long 2001, Janssen et al. 2005, Centers for Disease Control and Prevention 2016b, Kerr et al. 2017, Kowalski, Crocker & Donen 2004, Catlin, Simoes & Brownson 2003, SIP 4-99 Research Group 2002, The IPAQ group 2002).

Conclusion

Children in more densely populated neighborhoods with a higher probability of unhealthy food store presence were more likely to consume sweet snacks and SSBs and to walk to destinations. They were also more likely to be overweight/obese in spite of the greater prevalence of active transportation. Healthy changes to the food environment in these types of neighborhoods may be more important than they are in low walkable areas due to greater food accessibility by children who utilize walking as a mode of transportation. Recognizing and leveraging beneficial aspects of neighborhood patterns may be more effective at positively influencing children's eating and PA behaviors compared to isolating individual aspects of the built environment. As studies using LCA accumulate, patterns will continue to emerge and consistent ones will inform strategies that can be targeted at specific neighborhood types to improve residents' health.

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Highlights

- Food and physical activity behaviors are influenced by environmental patterns.
- Children in dense urban neighborhoods may walk more and eat more unhealthy foods.
- Improved food environments can benefit children who walk for transportation.

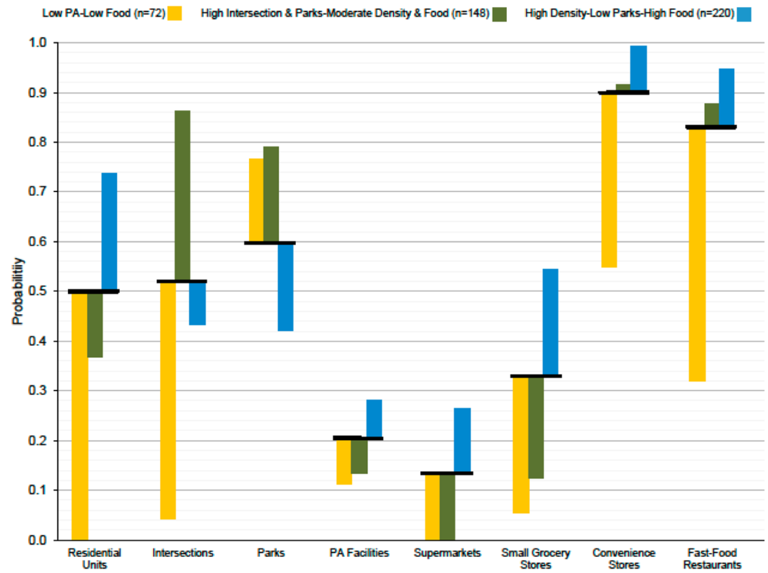
Low PA-Low Food (n=72)
High Intersection & Parks-Moderate Density & Food (n=148)
High Density-Low Parks-High Food (n=220)
Probability
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
Residential Units
Intersections
Parks
PA Facilities
Supermarkets
Small Grocery Stores
Convenience Stores
Fast-Food Restaurants

Figure 1.

Table 1

Proportions of Dichotomous Neighborhood Characteristics prior to LCA

Residential Units (count, median = 965)	50.0%
Intersections (count, median = 39)	52.0%
Presence of Supermarket	13.4%
Presence of Small Grocery Store	32.8%
Presence of Large Park	59.8%
Presence of Convenience Store	90.0%
Presence of Fast Food	82.9%
Presence of PA Facility	20.5%

Table 2

Average Maximum Posterior Probabilities of Class Membership (row) by Latent Class (column)

	Low PA-Low Food (n=72) M(±SD)	**High Intersection & Parks-Moderate Density & Food (n=148) M(±SD)**	**High Density-Low Parks-High Food (n=220) M(±SD)**
Classified into:			
Low PA-Low Food (n=72)	0.82 (0.22)	0.13 (0.15)	0.06 (0.08)
High Intersection & Parks-Moderate Density & Food (n=148)	0.02 (0.03)	0.80 (0.13)	0.19 (0.14)
High Density-Low Parks-High Food (n=220)	0.02 (0.07)	0.10 (0.12)	0.87 (0.15)

Entropy = 0.652 for the LCA supporting a 3-class solution

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Table 3

Summary statistics of child, parent, and block group characteristics overall and by latent class

	Overall (n=404)[a]	Low PA-Low Food (n=69)	High Intersection & Parks-Moderate Density & Food (n=137)	High Density-Low Parks-High Food (n=198)
	Percent/Mean ±SD			
Child characteristics				
Age (years)	10.87 ±4.38	10.32 ±4.56	11.04 ±4.17	10.94 ±4.46
Male (%)	52	71[b]	50[c]	47[c]
Race				
Non-Hispanic white (%)	7	12	4	8
Non-Hispanic black (%)	49	51	53	46
Hispanic (%)	44	38	43	46
Parent characteristics				
Education				
High school or less (%)	61	52[b]	69[c]	58[b,c]
Some college (%)	25	23	25	26
Bachelor’s or higher (%)	14	25[b]	7[c]	16[b]
Foreign-born (%)	8	6	5	11
Poverty (mean % FPL[d])	232	376[b]	221[c]	190[c]
Block group characteristics				
Majority Race				
Non-Hispanic white (%)	13	15	11	13
Non-Hispanic black (%)	44	46	46	41
Hispanic (%)	39	34[b]	37[b,c]	42[c]
Majority Education				
High school or less (%)	69	61	69	71
Some college (%)	20	22[b]	21[b]	18[c]
Bachelor’s or higher (%)	11	17[b]	10[c]	11[c]
Total Crime Index[e]	305.60	280.84[b]	349.50[c]	283.85[b]
Household income ($/1000)	36.9 ±16.2	42.2 ±20.1[b]	34.6 ±16.1[c]	36.5 ±14.4[c]

[a] Sample with no missing demographic or outcome variables;

[b,c] Values with differing superscripts differ significantly (*p*<.05)

[d] Federal poverty level;

[e] National average indexed at 100

Table 4

Summary statistics of children's behaviors and weight outcomes by latent class

	Overall (n=404)[a]	Low PA-Low Food (n=69)	High Intersection & Parks-Moderate Density & Food (n=137)	High Density-Low Parks-High Food (n=198)
	Percent/Mean ±SD (Median/Interquartile range)			
Healthy food intake				
Vegetables (x per day)	1.85 ±1.47 (1.53/1.29)	1.81 ±1.30 (1.33/1.28)	1.84 ±1.59 (1.57/1.29)	1.88 ±1.45 (1.54/1.29)
Fruits and vegetables (x per day)	4.50 ±3.03 (3.72/2.91)	5.04 ±3.41 (3.70/3.38)	4.44 ±3.15 (3.72/2.85)	4.35 ±2.78 (3.72/3.05)
Unhealthy food intake				
Fast food (x per week)	1.16 ±1.54 (0.90/0.50)	1.23 ±1.78 (1.00/0.70)	1.22 ±1.74 (1.00/0.50)	1.08 ±1.27 (0.90/0.80)
Salty snacks (x per day)	0.47 ±.0.90 (0.29/0.36)	0.39 ±0.49 (0.29/0.30)	0.53 ±0.92 (0.29/0.64)	0.46 ±0.99 (0.29/0.36)
Sugar-sweetened beverages (x per day)	1.13 ±1.49 (0.79/1.00)	0.93 ±1.13 (0.79/0.87)	1.22 ±.1.61 (1.00/1.02)	1.14 ±1.51 (0.71/1.15)
Sweets (x per day)	0.53 ±0.85 (0.29/0.57)	0.41 ±0.40 (0.29/0.43)	0.58 ±0.93 (0.29/0.86)	0.53 ±0.91 (0.29/0.61)
Physical Activity				
Physically active 7 days per week (%)[b]	26	29	26	25
Walk or bike to school sometimes (%)[c]	46	37	46	49
Walk to destinations often (%)[d]	28	18[e]	31[f]	30[e,f]
Weight status				
Overweight/obese[g] (%)	36	20[e]	41[f]	38[f]

[a]Sample with no missing demographic or outcome variables;

[b]Versus physically active fewer than 7 days per week;

[c]Versus never walk or bike to school;

[d]Versus walk to destinations less often;

[e,f]Values with differing superscripts differ significantly (p<.05);

[g]BMI above 85th percentile

Table 5

Negative binomial regression predicting healthy and unhealthy food outcomes by latent class

	Model 1			Model 2			Model 3		
	PR	95% CI	p-value	PR	95% CI	p-value	PR	95% CI	p-value
Vegetables (x per day) (n=391)									
Low PA-Low Food (referent)	1.0			1.0			1.0		
High Intersection & Parks-Moderate Density & Food	1.02	0.95–1.10	0.598	**0.94**	0.90–0.99	0.026	0.99	0.88–1.11	0.842
High Density-Low Parks-High Food	1.04	0.91–1.19	0.543	0.97	0.87–1.08	0.554	1.01	0.92–1.11	0.818
Fruits and vegetables (x per day) (n=384)									
Low PA-Low Food (referent)	1.0			1.0			1.0		
High Intersection & Parks-Moderate Density & Food	0.88	0.73–1.06	0.186	0.89	0.75–1.05	0.176	0.93	0.79–1.09	0.378
High Density-Low Parks-High Food	0.86	0.72–1.04	0.122	0.87	0.73–1.05	0.146	0.91	0.74–1.11	0.333
Fast food (x per week) (n=399)									
Low PA-Low Food (referent)	1.0			1.0			1.0		
High Intersection & Parks-Moderate Density & Food	0.99	0.79–1.26	0.963	1.00	0.84–1.21	0.962	1.00	0.91–1.10	0.963
High Density-Low Parks-High Food	0.88	0.54–1.43	0.609	0.90	0.60–1.37	0.630	0.99	0.76–1.29	0.965
Salty snacks (x per day) (n=397)									
Low PA-Low Food (referent)	1.0			1.0			1.0		
High Intersection & Parks-Moderate Density & Food	**1.36**	1.13–1.64	0.001	1.14	0.98–1.33	0.095	1.14	0.89–1.46	0.303
High Density-Low Parks-High Food	1.19	0.93–1.51	0.173	1.02	0.79–1.32	0.865	1.00	0.79–1.26	0.997
Sugar-sweetened beverages (x per day) (n=392)									
Low PA-Low Food (referent)	1.0			1.0			1.0		
High Intersection & Parks-Moderate Density & Food	1.32	0.95–1.82	0.097	1.25	0.99–1.58	0.057	**1.33**	1.08–1.64	0.008
High Density-Low Parks-High Food	**1.23**	1.02–1.48	0.31	**1.18**	1.05–1.33	0.006	**1.27**	1.09–1.47	0.002

	Model 1			Model 2			Model 3		
	PR	95% CI	p-value	PR	95% CI	p-value	PR	95% CI	p-value
Sweets (x per day) (n=395)									
Low PA-Low Food (referent)	1.0			1.0			1.0		
High Intersection & Parks-Moderate Density & Food	**1.41**	1.07–1.88	0.016	**1.42**	1.03–1.97	0.032	1.37	0.89–2.09	0.150
High Density-Low Parks-High Food	**1.29**	1.01–1.65	0.038	1.30	0.95–1.77	0.103	1.24	0.91–1.70	0.176

Model 1 includes only LCA membership; Model 2 includes LCA membership and child/parent level variables (sex, age, race/ethnicity, education, immigration status, family income); Model 3 includes LCA membership, child/parent level variables, and block group characteristics (race/ethnicity, education, total crime index, median income); Sample with non-missing values included in analyses; Bold if significant at p<.05.

Table 6

Binomial regression predicting physical activity and weight outcomes by latent class

	Model 1			Model 2			Model 3		
	OR	95% CI	p-value	OR	95% CI	p-value	OR	95% CI	p-value
Physically active (7 days/wk vs less than 7 days/wk) (n=404)									
Low PA-Low Food (referent)	1.0			1.0			1.0		
High Intersection & Parks-Moderate Density & Food	0.87	0.32–2.37	0.790	0.83	0.35–1.97	0.677	0.80	0.34–1.89	0.616
High Density-Low Parks-High Food	0.83	0.35–1.95	0.665	0.89	0.42–1.90	0.763	0.89	0.41–1.93	0.771
Walk or bike to school (at least 1 day/wk vs 0 days/wk) (n=396)									
Low PA-Low Food (referent)	1.0			1.0			1.0		
High Intersection & Parks-Moderate Density & Food	**1.45**	1.04–2.02	0.028	1.10	0.85–1.43	0.453	0.92	0.64–1.34	0.676
High Density-Low Parks-High Food	**1.63**	1.17–2.27	0.004	1.43	0.98–2.09	0.065	1.28	0.90–1.80	0.165
Walk to destinations (often vs less than often) (n=402)									
Low PA-Low Food (referent)	1.0			1.0			1.0		
High Intersection & Parks-Moderate Density & Food	2.09	0.75–5.79	0.158	1.72	0.83–3.54	0.144	1.55	0.77–3.14	0.223
High Density-Low Parks-High Food	**1.98**	1.02–3.83	0.043	**1.92**	1.24–2.98	0.004	**1.78**	1.15–2.77	0.010
Overweight/obese (normal weight vs overweight/obese) (n=404)									
Low PA-Low Food (referent)	1.0			1.0			1.0		
High Intersection & Parks-Moderate Density & Food	**2.72**	1.86–3.96	<.001	**2.55**	2.02–3.23	<.0001	**2.29**	1.62–3.26	<.001
High Density-Low Parks-High Food	**2.45**	1.35–4.45	0.003	**2.60**	1.62–4.19	<.0001	**2.48**	1.58–3.88	<.001

Model 1 includes only LCA membership; Model 2 includes LCA membership and child/parent level variables (sex, age, race/ethnicity, education, immigration status, family income); Model 3 includes LCA membership, child/parent level variables, and block group characteristics (race/ethnicity, education, total crime index, median income); Sample with non-missing values included in analyses; Bold if significant at p<.05.