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Patterns of Obesogenic Neighborhood Features and Adolescent Weight

A Comparison of Statistical Approaches

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Background: Few studies have addressed the potential influence of neighborhood characteristics on adolescent obesity risk, and findings have been inconsistent.

Purpose: Identify patterns among neighborhood food, physical activity, street/transportation, and socioeconomic characteristics and examine their associations with adolescent weight status using three statistical approaches.

Methods: Anthropometric measures were taken on 2682 adolescents (53% female, mean age=14.5 years) from 20 Minneapolis/St. Paul MN schools in 2009–2010. Neighborhood environmental variables were measured using GIS data and by survey. Gender-stratified regressions related to BMI *z*-scores and obesity to (1) separate neighborhood variables; (2) composites formed using factor analysis; and (3) clusters identified using spatial latent class analysis in 2012.

Results: Regressions on separate neighborhood variables found a low percentage of parks/recreation, and low perceived safety were associated with higher BMI *z*-scores in boys and girls. Factor analysis found five factors: away-from-home food and recreation accessibility, community disadvantage, green space, retail/transit density, and supermarket accessibility. The first two factors were associated with BMI *z*-score in girls but not in boys. Spatial latent class analysis identified six clusters with complex combinations of both positive and negative environmental influences. In boys, the cluster with highest obesity (29.8%) included low SES, parks/recreation, and safety; high restaurant and convenience store density; and nearby access to gyms, supermarkets, and many transit stops.

Conclusions: The mix of neighborhood-level barriers and facilitators of weight-related health behaviors leads to difficulties disentangling their associations with adolescent obesity; however, statistical approaches including factor and latent class analysis may provide useful means for addressing this complexity.
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Introduction

Most research linking neighborhood characteristics to obesity has been conducted in adult populations.[1] Relatively few studies[2–16] have addressed the potential influence of these factors on obesity risk among adolescents. Literature reviews[1,4] examining neighborhood environmental influences on obesity identify few consistent findings. Given the complex patterns of our built environments, a major methodologic challenge is simultaneously accounting for the numerous environmental variables that may be acting in synergistic or antagonistic ways leading to obesity.[17] For example, a neighborhood may include many fast-food restaurants but may also support utilitarian physical activity and provide ready access to recreation centers. There is grow-

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ing interest in disentangling environmental contributions to adolescent obesity[18,19] and a need for studies that consider a wide range of environmental variables along with their potential combined influence.

The goal of the current study is to take advantage of statistical methodology that comprehensively incorporates characteristics of complex neighborhood environments to elucidate relationships with obesity that could not be found by considering just one characteristic at a time. Using a large, population-based sample of middle and high school students in Minneapolis/St. Paul MN, the current study explored associations between adolescent weight status and a wide range of 22 neighborhood characteristics, including access to food sources, access to recreational places, opportunities for utilitarian physical activity, perceived safety, and neighborhood sociodemographics.

Three distinct but complementary statistical analyses were employed: (1) regression on separate neighborhood characteristics; (2) exploratory factor analysis examining whether these neighborhood characteristics could be combined into a smaller set of factors associated with adolescent weight status; and (3) latent class analysis to identify clusters of obesogenic neighborhood profiles and test their associations with adolescent weight status. These different statistical methods were considered in order to fully explore potential complex relationships among neighborhood characteristics and their potential combined impact on risk for obesity.

Methods

Sample and Study Design

Data were drawn from Eating and Activity in Teens (EAT) 2010, a population-based study examining diet and physical activity behaviors, weight status, and factors associated with these outcomes. The study population included adolescents from 20 public middle schools and high schools in the Minneapolis/St. Paul metropolitan area of Minnesota, which serve socioeconomically and racially/ethnically diverse communities. There were 2682 adolescents who completed surveys and anthropometric measures during the 2009–2010 academic year and for whom GIS data were available to describe their neighborhood environments.

Mean participant age was 14.5 years (SD=2.0); 45.1% were in middle school (6th–8th grades) and 54.9% were in high school (9th–12th grades). Participants were equally divided by gender (53.5% girls). Racial/ethnic backgrounds represented were as follows: 18.7% white, 29.2% African-American or black, 20.1% Asian-American, 17.1% Hispanic, 3.4% Native American, and 11.5% mixed or other. Trained research staff administered surveys in classrooms and measured adolescents' height and weight following standardized procedures.[20] All study procedures were approved by the University of Minnesota's IRB and by the participating school districts.

Individual Sociodemographic Measures and BMI *z*-Score

Adolescent participants self-reported their gender, age, race/ethnicity, and SES. SES was determined primarily using the higher education level of either parent. To address possible misclassification of participants facing economic distress as high SES based on parental education, an algorithm was developed that also took into account family eligibility for public assistance, eligibility for free or reduced-cost school meals, and parental employment status.[21,22] BMI was calculated and gender- and age-specific percentiles were determined using reference data from the CDC growth tables in order to classify respondents as obese (BMI ≥95th percentile) and to calculate BMI *z*-scores.[23] BMI *z*-scores represent the number of SDs a participant's BMI is above (positive) or below (negative) the standard population mean.

Neighborhood Environment Assessment

All neighborhood environmental variables were measured using GIS data, except for perceived neighborhood safety, which was collected from adolescents via two survey items from the Neighborhood Environment Walkability Scale.[24,25] Adolescents indicated their agreement with the statement "The crime rate in my neighborhood makes it unsafe to go on walks during the day" and a similar statement about walking at night. One-week test–retest agreement (n=129) was strong for both daytime (82%) and nighttime (87%) safety. The two questions were combined and Likert-type responses were collapsed (somewhat or strongly disagree versus somewhat or strongly agree) yielding three categories: (1) safe environment; (2) unsafe only at night; and (3) unsafe during the day and night.

Neighborhood characteristics measured using GIS addressed (1) food access, specifically density of and distances to the nearest supermarket, convenience store, any restaurant, and fast-food restaurant; (2) opportunities for recreational physical activity, including proportion of nearby land used for parks/recreation and distances to the nearest walking/biking trail, recreation center, and gym/fitness center; (3) support for utilitarian physical activity, including number of street access points, proportion of nearby streets that are "busy" (i.e., highways and connecting streets), density of public transit stops, and proportion of land used for commercial buildings; and (4) neighborhood sociodemographics, including percentage of households headed by a single woman, people aged >25 years with a high school degree, households in poverty, and people aged <18 years as well as median household income. ArcGIS, version 9.3.1, was used for geocoding each participant's home address. GIS data sources used for creating features included U.S. Census data (Year 2000 Census tracts boundaries using 2005–2009 American Community Survey 5-year estimates)[26]; land-use data; transit route data from MetroGIS[27]; and commercial databases (accessed through Esri Business Analyst, 2010).[28]

Geographic information system neighborhood variables were created uniquely for each participant using buffers centered at the participant's home address with the exception of neighborhood sociodemographics, which were summarized at the census-tract level. Straight-line distances were used for calculating access to nearest walking/biking trail, and straight-line buffers were used to examine the proportion of land used for parks/recreation and commercial buildings. All other distances and densities were derived using the automobile-accessible road network to define routes between a participant's home and particular destinations.

Densities were calculated using 1600-m (approximately 1-mile) buffers centered at a participant's home and dividing the total number of destinations by the land area. Buffer distances of 1600 m were selected, as prior research has found that adolescents perceive an easy walking distance to be of about 15 minutes' duration (i.e., 1600-m walking at a moderate pace) and the average participant in this study was not of driving age.[29] Additional details for neighborhood environment measures have been previously published.[30]

Statistical Analysis

In total, 22 neighborhood variables (21 GIS measures and one perceived measure) were examined. All GIS neighborhood variables were initially measured on a continuous scale but were categorized based on quartiles or dichotomized at prespecified cutpoints in some analyses to facilitate interpretation and to avoid the influence of outlying values arising from the right skew inherent in measures. Three different, but complementary, statistical analyses were employed, as described below.

Multiple linear regression. This analysis was used to examine the relationship between BMI z-score and each neighborhood characteristic dichotomized at its median value. In addition, different dichotomous cut-offs of distance to nearest food sources (one or more within 400, 800, or 1200 m) were tested to identify potential walking distance tipping points. Sensitivity analyses were conducted to identify trends across quartiles as compared to median splits of neighborhood characteristics. Gender-stratified regressions included only one neighborhood characteristic at a time and controlled for adolescent age in years, SES, and race/ethnicity. This type of analysis provides information about how each specific neighborhood variable may be associated with weight status and allows comparison with previous research using traditional regression methods.

Exploratory factor analysis. This analysis of the 22 neighborhood variables treated as continuous measures was conducted with promax rotation in SAS Proc Factor. In addition to interpretability of factors, the number of eigenvalues >1 and the percentage variability explained were used to choose the number of factors. Factor scores were calculated and then used in gender-stratified regressions of BMI z-score controlling for adolescent age, SES, and race/ethnicity.

This type of analysis provides an empirical way to identify which neighborhood variables are covarying similarly across the region. The factors that are found represent commonalities among neighborhood variables (e.g., park/recreation space and trails would logically be expected to co-locate and thus covary in a way that indicates they might be usefully combined rather than being treated as separate entities). Presumably then, these composite features may make more-salient predictors of adolescent weight status as they incorporate more complexity. The potential disadvantage can be the somewhat unspecific nature of the factor composite.

Spatial latent class analysis. This analysis[31] identified clusters of individual residences with similar patterns of the 22 neighborhood characteristics. Because latent class analysis clusters residences with similar neighborhood characteristics, and typically residences nearby each other have similar values on those characteristics (particularly through the use of network buffers centered at the residences), it follows that predicted latent class memberships will tend to cluster spatially (i.e., geographically). An independence model that allows posterior predicted latent class memberships to be completely determined by the profile of neighborhood characteristics was used. All variables were categorized by quartile (except perceived safety, which had three levels) in the latent class analysis, and estimates were obtained using maximum likelihood assuming conditional independence in Mplus, version 6.1. Choice of number of classes (clusters) relied primarily on the Bayesian information criterion (BIC), which balances model fit and parsimony.

Qualitative descriptions of the resulting neighborhood cluster profiles were based on summaries for each neighborhood variable within a cluster described as high/low if the majority of the individuals in that cluster were above or below the sample median. The point location of cluster-labeled residences were randomly perturbed for presentation on a map of the Minneapolis/St. Paul area (Figure 1) to ensure confidentiality.[32,33] Finally, given the predicted latent class membership (i.e., cluster category) for each individual adolescent residence, logistic regression of adolescent obesity status on their cluster category was performed adjusting for their age, SES, and race.

Adjusted prevalences of obese adolescents within each cluster were obtained by back-transforming the logistic regression adjusted means from the logit to the probability scale using SAS Proc Genmod and the inverse link transformation (ILINK option) in the LSMEANS (least-squares means of the group effect on the logit scale) statement. Latent class analysis provides an empirical way of clustering residences with similar combinations of neighborhood characteristics; however, interpreting or labeling these clusters can be difficult, because of their complex mix of environmental variables.

Results

Associations of Adolescent BMI *z*-Score with Specific Neighborhood Characteristics: Regressions on Separate Variables

Table 1 presents the descriptive summary statistics for all of the neighborhood characteristics. Controlling for individual-level age, SES, and race/ethnicity, the neighborhood characteristics found to be significantly ($p<0.05$) associated with a higher BMI z-score among both boys and girls in regression analyses were lower proportion of park/recreation land and the perception of being unsafe during the day and night (Table 2). Additionally, among girls, decreased distance to the nearest restaurant, access to a convenience store within 1200 m, and more street access points were associated with higher BMI z-score. None of the five neighborhood sociodemographic variables were associated with BMI z-score after controlling for adolescent sociodemographics.

Obesogenic Factors—Composite Neighborhood Characteristics: Factor Analyses

Six eigenvalues were >1.0; the first five factors explained 66% of the variability and all six explained 71% of the variability in the 22 neighborhood characteristics. Exploratory factor analyses with five and six factors were

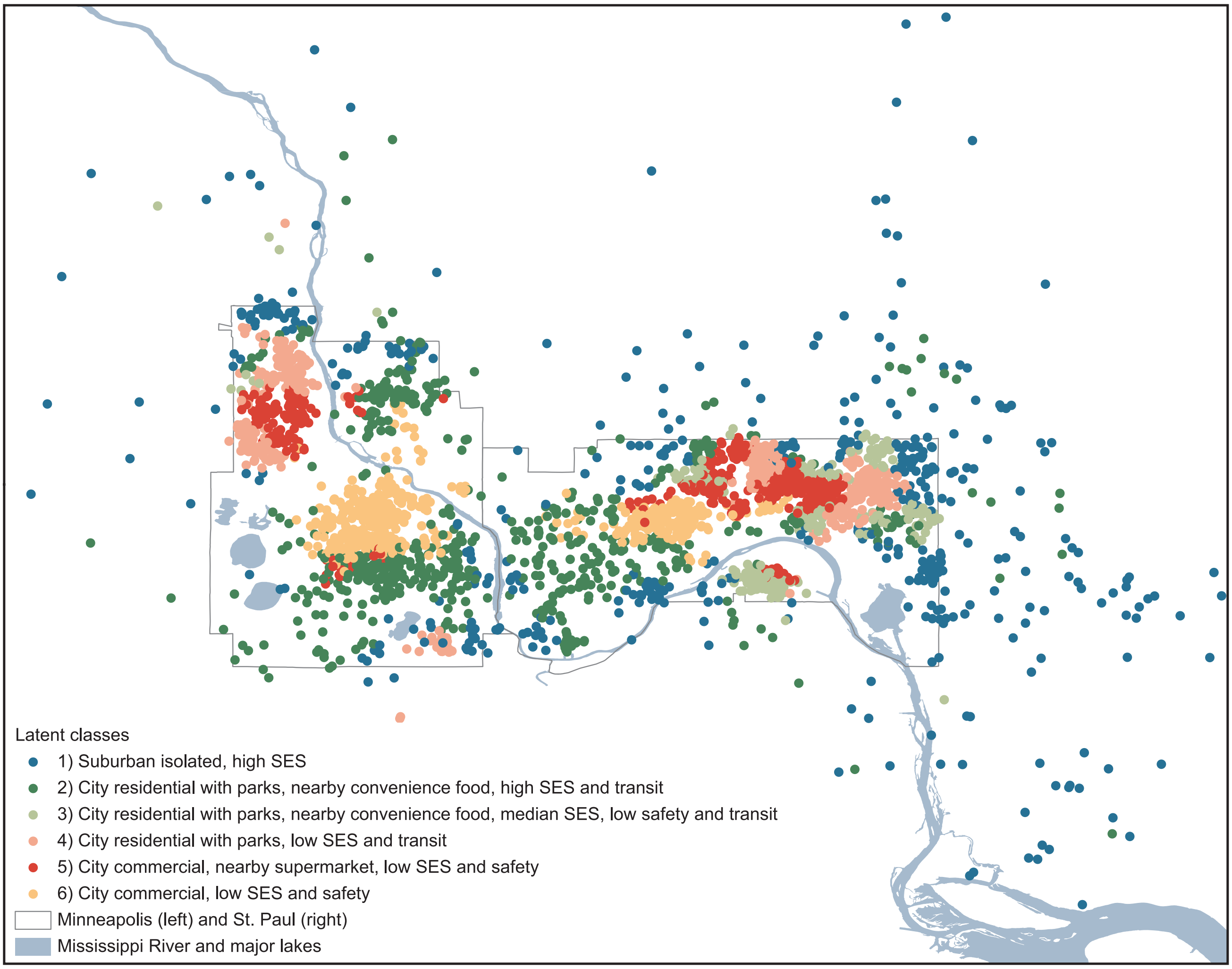

Figure 1. Map of Minneapolis/St. Paul MN with residences of EAT 2010 participants

Note: Residences of participants are indicated by points (randomly perturbed for privacy) and colored according to the six obesogenic neighborhood environmental clusters identified by spatial latent class analysis (see Table 5 for description of clusters).

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conducted and the six-factor solution was not found to provide additional interpretable factors beyond the five-factor model. Factor loadings (Table 3) were used to label the five factors as retail/transit density (related to higher density of convenience stores, restaurants, commercial buildings, transit stops and busy streets); away-from-home food and rec/fitness center accessibility (related to closer distance to convenience stores, restaurants, recreation and gym/fitness centers and more street access points); supermarket accessibility (related to closer and more supermarkets); community disadvantage (related to higher perceived lack of safety, and disadvantaged sociodemographic factors); and green space (related to higher percentage of land used for parks/recreation, closer walking/biking trails, fewer transit stops and access points yet more busy streets).

Associations between adolescent BMI *z*-score and obesogenic factors. Among boys and girls (Table 4), high scorers for community disadvantage had higher BMI *z*-scores in Model 1; however, the association was significant only for girls in Model 2 controlling for individual-level sociodemographics. Among girls, high scorers on access to away-from-home food and rec/fitness center and low scorers on green space had higher BMI *z*-scores in Model 1, but the association only remained significant for access to away-from-home food and rec/fitness center after controlling for adolescent sociodemographics.

Obesogenic Clusters—Identifying Neighborhood Profiles: Spatial Latent Class Analyses

Spatial latent class analysis identified six clusters with differing neighborhood characteristics (Table 5). Com-

Table 1. Descriptive statistics for residential neighborhood characteristics of n=2682 adolescents

	M (SD)	25th percentile	Median	75th percentile	Minimum	Maximum
Density of food outlets (count per square km)[a]						
Supermarkets	0.07 (0.15)	0.00	0.00	0.00	0.00	1.14
Convenience stores	1.03 (0.55)	0.66	1.00	1.36	0.00	5.59
All restaurants	4.45 (4.61)	1.65	3.20	5.48	0.00	58.14
Fast-food restaurants	1.23 (1.08)	0.55	1.05	1.62	0.00	12.29
Distance to nearest food outlets (m)						
Supermarket	2573 (1197)	1741	2460	3318	126	13,338
Convenience store	741 (493)	419	660	949	4	6,912
Any restaurant	601 (478)	295	495	768	0	6,665
Fast-food restaurant	899 (596)	495	794	1155	13	7,110
Recreational places						
Distance to recreation center (m)	715 (535)	391	596	865	0	5490
Distance to gym/fitness center (m)	1675 (974)	952	1520	2180	0	7857
Distance to walking/biking trail (m)	492 (369)	226	400	667	4	4698
Park/recreation space (% of area)[b]	9.5 (7.4)	4.7	7.0	12.2	0.1	50.6
Streets/transportation/commerce						
Transit stop density (count per square km)[a]	17.8 (6.3)	14.3	17.6	21.3	0.0	54.8
Access points (count)[a]	66 (17)	56	69	79	3	103
Busy streets (% of streets)[a]	19.7 (9.5)	12.9	17.4	25.4	0.0	80.7
Commercial building space (% of area)[b]	6.1 (4.2)	3.1	5.1	8.0	0.0	31.7
Perceived lack of safety (%)[c]						
Safe day and night	55.0	—	—	—	—	—
Unsafe only at night	23.0	—	—	—	—	—
Unsafe during the day and night	22.0	—	—	—	—	—
Neighborhood sociodemographics[d]						
Households headed by women (%)	17.8 (9.0)	10.8	16.6	22.9	0.00	46.4
High school graduates (%)	81.4 (10.7)	73.7	81.7	89.9	50.5	100.0
Median household income (2009 dollars)	42,963 (16,933)	32,438	40,528	51,935	12,188	126,458
Households in poverty (%)	21.0 (13.0)	10.6	18.7	29.5	0.0	63.7
Aged ≤17 years (%)	28.4 (8.9)	21.2	28.4	34.4	1.5	50.5

[a]Within a 1600-m network buffer
[b]Within a 1600-m straight-line buffer
[c]Self-reported by adolescent
[d]Within Year 2000 U.S. Census-tract boundaries using 2005–2009 American Community Survey 5-year estimates: www.census.gov/acs/www/data_documentation/2009_release/; (309 unique census tracts represented).

pared to models with fewer classes, the BIC model comparison statistic for the six-class model was superior. Although the latent class model with seven classes had a better BIC than the six-class model, it did not partition the data into further qualitatively distinct classes and also reached boundary values for some parameters indicating instability. The distribution of the six clusters is mapped in Figure 1.

Two of the clusters represented neighborhoods with relatively higher SES and higher perceived safety (Clusters 1 and 2). Cluster 1, "suburban isolated, high SES," located on the map outside (or near) the city lines

Table 2. Associations between neighborhood characteristics and adolescent BMI z-score adjusted for adolescent age, SES, and race/ethnicity

	Boys (n=1246)		Girls (n=1436)	
	β (SE)[a]	p-value	β (SE)[a]	p-value
Density of food outlets[b]				
Supermarkets	−0.013 (0.077)	0.871	0.046 (0.062)	0.454
Convenience stores	0.003 (0.065)	0.958	0.037 (0.051)	0.465
All restaurants	−0.020 (0.066)	0.763	−0.026 (0.051)	0.608
Fast-food restaurants	0.097 (0.065)	0.136	−0.026 (0.051)	0.615
Distance to nearest food outlets[b]				
Supermarket	0.081 (0.065)	0.208	−0.005 (0.051)	0.920
Convenience store	−0.001 (0.065)	0.988	−0.073 (0.051)	0.153
Any restaurant	0.066 (0.065)	0.310	**−0.122 (0.051)**	**0.017**
Fast-food restaurant	−0.031 (0.065)	0.635	−0.028 (0.051)	0.586
Presence of food outlet within 1200 m[c]				
Supermarket	−0.071 (0.105)	0.502	0.069 (0.086)	0.422
Convenience store	0.190 (0.102)	0.063	**0.223 (0.078)**	**0.005**
Any restaurant	0.067 (0.120)	0.575	**0.202 (0.094)**	**0.032**
Fast-food restaurant	0.095 (0.078)	0.222	0.045 (0.060)	0.458
Recreational places[b]				
Distance to recreation center	0.027 (0.065)	0.683	0.003 (0.051)	0.959
Distance to gym/fitness center	0.018 (0.066)	0.783	0.023 (0.051)	0.651
Distance to walking/biking trail	−0.041 (0.065)	0.522	0.065 (0.051)	0.207
Park/recreation space (% of area)	**−0.161 (0.066)**	**0.014**	**−0.129 (0.051)**	**0.012**
Streets/transportation/commerce[b]				
Transit stop density	0.041 (0.067)	0.540	−0.037 (0.052)	0.475
Access points	−0.025 (0.066)	0.703	**0.106 (0.052)**	**0.039**
Busy streets	0.074 (0.065)	0.259	−0.093 (0.051)	0.068[d]
Commercial building space	0.034 (0.066)	0.606	0.045 (0.051)	0.384
Perceived lack of safety				
Unsafe only at night	−0.092 (0.081)	0.259	0.105 (0.063)	0.096
Unsafe during the day and night	**0.204 (0.088)**	**0.020**	**0.210 (0.063)**	**0.001**
Neighborhood sociodemographics[b]				
Households headed by women	−0.030 (0.068)	0.661	0.021 (0.054)	0.696
High school graduates	0.045 (0.069)	0.513	−0.087 (0.053)	0.102
Median household income	−0.096 (0.070)	0.170	−0.035 (0.054)	0.511
Households in poverty	0.003 (0.070)	0.967	0.084 (0.054)	0.115
Aged ≤ 17 years	0.058 (0.068)	0.400	0.095 (0.052)	0.071[d]

[a]Estimates are from separate linear regressions of BMI z-score on specific neighborhood characteristic adjusted for adolescent age, SES, and race/ethnicity; significant associations ($p<0.05$) are shown in bold.

[b]Neighborhood characteristics dichotomized at the median (0=below median, 1=above median); see footnote d.

[c]Cut-points of 400, 800, and 1200 m were all considered, but only 1200 m showed an effect for convenience store, 800 m also showed an effect for any restaurants, in girls, in the same direction.

[d]Additional regressions used neighborhood characteristic categorized into quartiles. All median dichotomized neighborhood characteristics were also found to be significant when using quartiles. Additional ($p<0.05$) trends were found using quartiles (identified with a superscript d). Direction of trend by quartile was same as direction of dichotomous effect.

Table 3. Factor loadings relating specific neighborhood characteristics to five continuous neighborhood composite factors[a,b]

	Retail/transit density	Away-from-home food and recreation/ fitness center accessibility	Supermarket accessibility	Community disadvantage	Green space
Density of food outlets					
Supermarkets	0.19	−0.12	**0.88**	−0.14	0.05
Convenience stores	**0.51**	0.21	0.18	0.04	−0.01
All restaurants	**0.93**	0.02	0.01	−0.11	−0.08
Fast-food restaurants	**0.85**	−0.01	0.12	−0.13	−0.04
Distance to nearest food outlets					
Supermarket	−0.05	−0.19	**−0.77**	−0.09	−0.07
Convenience store	0.04	**−0.89**	0.03	0.01	−0.18
Any restaurant	−0.11	**−0.88**	0.03	0.08	−0.14
Fast-food restaurant	−0.16	**−0.77**	−0.04	0.01	−0.16
Recreational places					
Distance to recreation center	**0.30**	**−0.69**	−0.06	−0.11	0.18
Distance to gym/fitness center	**−0.39**	**−0.39**	0.11	0.19	0.02
Distance to walk/bike trail	0.04	−0.28	−0.15	−0.05	**−0.81**
Park/recreation space	−0.28	0.04	−0.13	−0.26	**0.49**
Streets/transportation/commerce					
Transit stop density	**0.52**	**0.31**	−0.20	0.13	**−0.37**
Access points	0.15	**0.42**	0.18	0.25	**−0.36**
Busy streets	**0.61**	−0.23	−0.07	0.19	**0.48**
Commercial building space	**0.88**	−0.07	0.16	0.07	0.03
Perceived lack of safety					
Unsafe during night or day	−0.05	0.03	0.01	**0.35**	−0.12
Neighborhood sociodemographics					
Households headed by women	−0.24	−0.01	0.07	**0.85**	−0.01
High school graduates	−0.12	−0.00	0.14	**−0.86**	0.02
Median household income	−0.18	−0.18	0.10	**−0.75**	−0.10
Households in poverty	0.23	−0.01	−0.08	**0.82**	0.09
Aged ≤17 years	**−0.32**	−0.16	0.15	**0.86**	−0.02
Correlation between factors[c]					
Density of retail and transit	1				
Accessibility of eating-out food and recreation/ fitness centers	0.33	1			
Accessibility of supermarket	0.09	0.27	1		
Community disadvantage	0.20	0.25	0.09	1	
Green space	−0.00	−0.26	−0.13	−0.12	1

[a]All neighborhood characteristics were taken to be continuous measures including perceived safety which was defined at three levels (0=safe, 1=unsafe only at night, 2=unsafe during day and night).
[b]Principal components factor analysis with promax oblique rotation was used, and factor loadings >0.30 in absolute value are shown in bold to facilitate interpretation of factor.
[c]Pearson correlation between composite factor scores

Table 4. Associations between BMI *z*-score and standardized continuous neighborhood composite factors from factor analysis shown in Table 3

	Boys				Girls			
	Model 1		Model 2		Model 1		Model 2	
	β (SE)	*p*-value	β (SE)	*p*-value	β (SE)	*p*-value	β (SE)	*p*-value
Retail/transit density	0.042 (0.033)	0.214	0.026 (0.034)	0.451	0.006 (0.026)	0.817	−0.022 (0.026)	0.399
Away-from-home food and recreation/fitness center accessibility	0.040 (0.035)	0.264	0.005 (0.035)	0.881	**0.094 (0.025)**	**<0.001**	**0.070 (0.025)**	**0.005**
Supermarket accessibility	−0.032 (0.033)	0.327	−0.030 (0.032)	0.359	0.031 (0.026)	0.246	0.038 (0.026)	0.144
Community disadvantage	**0.073 (0.033)**	**0.025**	0.003 (0.037)	0.940	**0.087 (0.026)**	**0.001**	**0.065 (0.028)**	**0.021**
Green space	−0.008 (0.034)	0.821	0.018 (0.033)	0.580	**−0.065 (0.026)**	**0.012**	−0.048 (0.026)	0.062

Note: Estimates based on separate linear regressions of BMI *z*-score on each standardized continuous neighborhood composite factor adjusted for adolescent age (Model 1) and additionally adolescent SES and race/ethnicity (Model 2). Significant associations ($p<0.05$) are shown in bold.

emerged with low commercial business, limited transit, and long distances to all food sources and recreational facilities, but a high percentage of park/recreation land. Cluster 2, "city residential with parks, nearby convenience food, high SES and transit," described relatively affluent residential neighborhoods in the south center of the metropolitan area. Like other city clusters, Cluster 2 was near convenience stores and fast-food restaurants, but commercial density was low and there was relatively high percentage of park/recreation land, nearby recreational and gym/fitness facilities, and access to many transit stops. A middle-SES cluster with low safety emerged "city residential with parks, nearby convenience food, median SES, low safety and transit" (Cluster 3) and was similar to Cluster 2 in other respects but with low safety and transit.

The other three clusters represented more socioeconomically disadvantaged neighborhoods with lower perceived safety (Clusters 4–6). Cluster 4, "city residential with parks, low SES, and low transit," had relatively higher park/recreation land (at 7.6% compared to sample median of 7.0%) and was somewhat isolated with a longer median distance to nearest supermarket and low densities of fast food and transit. The other two more socioeconomically disadvantaged clusters were commercially dense with nearby and dense convenience foods, low park/recreation land, and high transit. A distinguishing characteristic of these two geographically centrally located clusters was nearby supermarket access: "city commercial, nearby supermarket, low SES and safety" (Cluster 5) and "city commercial, low SES and safety" (Cluster 6).

Associations of adolescent obesity with obesogenic neighborhood clusters. The prevalence of adolescent boys and girls categorized as obese (BMI ≥95th percentile) was compared across the six neighborhood clusters, adjusting for individual-level age, race/ethnicity, and SES (Table 6). Among boys living in Cluster 6, "city commercial, low SES and safety," 29.8% were obese, which was significantly higher than the 21.3% of obese boys living in Cluster 2, "city residential with parks, nearby convenience food, high SES and transit." Among girls living in Cluster 5, "city commercial, nearby supermarket, low SES and safety," 27.8% were obese, which was significantly higher than every other cluster.

Discussion

Using three different statistical methods, the present study examined a wide variety of neighborhood characteristics with the potential to influence adolescent weight status. Regression analyses identified specific variables associated with BMI *z*-score but did not facilitate interpretation of an overall environmental effect or the interconnections of multiple environmental variables. Factor analyses enabled assessment of the relative importance of highly correlated combinations of variables. Spatial latent class analysis combined SES and neighborhood variables and demonstrated the importance of SES combined with neighborhood characteristics in predicting obesity.

The different statistical analyses undertaken in the present paper together point to some similar conclusions; specifically, convenient access to unhealthy foods and lack of safe space for outdoor recreation in adolescents' neighborhoods were related to higher rates of obesity. When using the commonly employed method of regression on individual neighborhood characteristics, of the 21 GIS variables, only decreased park/recreation space was associated with higher BMI *z*-score in both boys and girls. Nearby access to convenience stores and restaurants was associated with higher BMI *z*-score in girls suggest-

Table 5. Description of six clusters identified using latent class analysis of neighborhood environmental variables[a]

"Cluster name" (% of sample)	Supermarkets	Convenience stores	Fast-food restaurants	Recreational places	Streets/transit/ commerce	Perceived safety (%)	HH income ($), education (% HS)[b]
High/medium neighborhood SES[b]							
"Suburban isolated, high SES" Cluster 1 (18.0%)	Long distance (3.0 km)	Long distance (1061 m), low density	Long distance (1411 m), low density	High park/recreation land (14.5%), long distance to gym or recreation centers	Low commerce (3.0%), low transit (11.8%) and few, but busy streets	High (73)[c]	High (57,000; 91)
"City residential with parks, nearby convenience food, high SES and transit" Cluster 2 (22.2%)	Median distance (2.4 km)	Short distance (552 m), median density	Short distance (604 m), median density	High park/recreation land (7.7%), short distance to recreation centers	Median commerce (5.5%), high transit (18.8%), high access but not busy streets	High (68)	High (52,000; 91)
"City residential with parks, nearby convenience food, median SES, low safety and transit" Cluster 3 (9.1%)	Long distance (3.3 km)	Median distance (645 m), median density	Short distance (631 m), high density	High park/recreation land (9.2%), short distance to gym	Median commerce (4.9%), low transit (15.9%) low street access not busy	Low (49)	Median (44,000; 80)
Low neighborhood SES[b]							
"City residential with parks, low SES and transit" Cluster 4 (15.5%)	Long distance (2.7 km)	Long distance (684 m), median density	Long distance (1085 m), low density	High park/recreation land (7.6%), long distance to gym or recreation centers	Low commerce (2.6%), low transit (16.9%), low street access not busy	Low (45)	Low (36,000; 77)
"City commercial, nearby supermarket, low SES and safety" Cluster 5 (16.0%)	Short distance (1.7 km)	Short distance (626 m), high density	Short distance (769 m), high density	Low park/recreation land (5.3%), short distance to gym	Median commerce (5.5%), high transit (18.4%), high access but not busy streets	Low (42)	Low (31,000; 73)
"City commercial, low SES and safety" Cluster 6 (19.1)	Median distance (2.4 km)	Short distance (568 m), high density	Short distance (605 m), high density	Low park/recreation land (5.0%), short distance to gym and recreation centers	High commerce (10.4%), high transit (23.5%), and many busy streets	Low (44)	Low (29,000; 73)

[a]Neighborhood characteristics were categorized in quartiles to perform spatial latent class analysis. Qualitative terms "low/high" and "short/long" describe median neighborhood characteristics in the particular cluster that are below or above (respectively) the overall median of the whole sample (shown in Table 1).
[b]Neighborhood SES is determined to be high, medium, or low based on five variables (two shown, three not shown): median HH income, percentage of residents aged >25 years with an HS degree, proportion of households headed by a woman, the proportion of households living in poverty, and the proportion of residents aged ≤17 years.
[c]Percentage adolescents reporting always feeling safe walking around their neighborhood during the day and night
HH, household; HS, high school

Table 6. Prevalence of obese adolescents (BMI ≥95th percentile) by clusters from latent class analysis of neighborhood environmental variables, % (SE)

Latent class	Cluster name	Boys		Girls	
		Model 1	Model 2	Model 1	Model 2
1	Suburban isolated, high SES	20.5 (2.8)[a]	22.2 (3.0)[a,b]	**16.0 (2.2)**[a]	16.7 (2.3)[a]
2	City residential with parks, nearby convenience food, high SES and transit	**20.8 (2.4)**[a]	**21.3 (2.6)**[a]	17.3 (2.2)[a]	16.5 (2.2)[a]
3	City residential with parks, nearby convenience food, median SES, low safety and transit	29.7 (4.3)[a,b]	27.5 (4.2)[a,b]	16.3 (3.2)[a]	**16.0 (3.2)**[a]
4	City residential with parks, low SES and transit	24.5 (3.2)[a,b]	22.4 (3.1)[a,b]	17.6 (2.5)[a]	17.1 (2.5)[a]
5	City commercial, nearby supermarket, low SES and safety	**31.1 (3.3)**[b]	28.4 (3.3)[a,b]	**27.8 (3.0)**[a]	**27.8 (3.1)**[b]
6	City commercial, low SES and safety	31.3 (3.0)[b]	**29.8 (3.0)**[b]	19.4 (2.5)[a]	16.8 (2.3)[a]

Note: Estimates based on logistic regression on six categorical clusters controlling for adolescent age (Model 1) and additionally adolescent-level SES and race/ethnicity (Model 2). Adjusted prevalences of obese adolescents were obtained by back-transforming the logistic regression adjusted means on the logit scale. Highest and lowest adjusted proportions are shown in bold within each model. See Table 5 and Figure 1 for description of clusters.

[a,b]Prevalences that do not have the same letters in their superscripts are statistically different from one another ($p<0.05$) (e.g., in Model 2 for boys, Classes 2 and 6 are the only ones significantly different).

ing girls may be more influenced by exposure to potentially unhealthy neighborhood food sources. Perceived lack of neighborhood safety during the day and night was also associated with higher BMI *z*-score in boys and girls. Similarly, factor analysis indicated that increased community disadvantage and less green space were both associated with higher BMI *z*-score in girls. Spatial latent class analysis likewise identified areas with these characteristics as being home to larger percentages of obese adolescents.

The statistical techniques utilized here also shed new light on ways in which the inter-relationships between environmental characteristics can be quite complex. Using spatial latent class analysis, six distinct clusters emerged with identifiably distinct neighborhood attributes and locations. Although other studies have shown that low-SES neighborhoods tend to have greater access to sources of energy-dense foods,[34,35] in the current urban sample, this also occurred in higher-SES areas (Clusters 2 and 3). Further, it was found that all three low-SES clusters had either high park land/recreation or were in proximity to recreational facilities. These findings, together with the factor analyses results, indicate the complexity of neighborhood structures.

Study strengths and weaknesses are important to consider in drawing conclusions. BMI was measured and a comprehensive set of neighborhood characteristics was derived based on state-of-the-art, standardized GIS protocols centered at participants' home residences. Going beyond conventional analyses for these types of data, extensive statistical analyses were performed to identify patterns of neighborhood characteristics that capture the complexity of the built environment as it relates to adolescent obesity. The large size and diversity of the sample are additional strengths. Study limitations include the following: all participants were drawn from urban schools within just one metropolitan area, data are cross-sectional, and possible classification and address errors in the GIS data.[36,37] Finally, given that neighborhood characteristics of cities differ, extrapolating health-related findings and determining the suitability of different analyses for other locations should be done cautiously. Replication is needed in different geographic areas.

Implications for Research and Practice

The results described here emphasize the complexity, and also the potential implications, of neighborhood-level disparities in access to food and opportunities for physical activity, and show associations between weight status and the built environment among youth from lower- versus higher-income areas.[9] Future studies should examine how built environment characteristics of neighborhoods tend to cluster in other geographic locations and consider how socioeconomic resources within communities affect the observed associations. Future analyses should also explore other environments inhabited by adolescents including neighborhoods surrounding schools.

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Supplementary data

A pubcast created by the authors of this paper can be viewed at www.ajpmonline.org/content/video_pubcasts_collection.