Health-related characteristics of American urban environments: Description, measurement, and associations with healthy behaviors

by

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Chapter 1:

Introduction

There exists a long American public health tradition of linking human health outcomes to residential environments and attempting to improve health outcomes by intervening on those environments. In the nineteenth century, the fields of public health and urban planning were unified in their efforts to improve health by intervening on residential environments that were deemed unhealthy. Though some of these interventions were based on the false theory of miasmic clouds of disease in crowded areas, policy changes to alleviate overcrowding and ensure interior ventilation were ultimately successful at improving health.[1, 2]

By the mid-20th century urban planning and public health began to employ divergent approaches to improving population health. With the advent of the germ theory of disease, public health efforts gradually shifted toward medicinal interventions on disease. As automobiles became the dominant mode of transportation, urban planning became more focused on the efficient movement of cars between areas with distinct land uses.[3, 4] Thus, in many American cities, the built environments constructed in the latter half of the century are loosely referred to as "suburban sprawl," which is typically characterized by separation of land uses into distinct zones and an emphasis on automobile travel.[3] Human health, though not entirely ignored, has not been a priority in the designs of these environments.

More recently, renewed interest in reconnecting these fields has spurred considerable academic research. A growing collection of research has found associations between a wide range of aspects of the built environment and an even wider range of health outcomes. These associations include access to recreational opportunities with insulin resistance,[5] time spent driving in cars with obesity,[6] neighborhood walkability indices with weight gain,[7] neighborhood traffic levels with physical activity,[8] and separation of land uses with both time and opportunities for physical activity.[9,10]

These studies contributed to our general understanding that human health is impacted by the environments in which we live, work, and play. But the actual mechanisms underlying the relationship between health, and especially healthy behaviors, and the environment are complex and not fully understood. Research in this field continues to expand and more attention is being focused on rigorously examining measures and addressing possible methodological limitations to earlier studies.[11,12] To further that discussion, this dissertation focuses on identifying how multiple health-related resources are patterned in environments, how their presence can be linked to healthy behaviors, and how important differences in environmental perception could be masked by commonly-used methodologies for quantifying the built environment. The following section reviews relevant literature that motivates these research questions.

Background

For the purposes of this dissertation, the term "built environment" refers to all aspects of the environment that have been made by humans for human use. This broad definition includes such things as roads, retail stores, sidewalks, and other features of the environment that people interact with and it has been used in other literature.[13] The range of environmental characteristics that have been explored in built environment and health research is far too great to be reviewed in its entirety here. Instead, this section focuses on reviewing recent research in three specific areas that are pertinent for this dissertation: 1) the demographic patterning of health-related resources and the possible contributions of these patterns to health inequities, 2) the links between resources and healthy behaviors, and 3) the examination of built environment measures.

Demographic patterning of health-related resources

Empirical evidence supports the idea that aspects of the built environment that potentially support or hinder healthy behaviors are not randomly distributed across our landscape. For example, numerous studies have found that poor and/or minority areas have stores offering poorer quality produce,[14] have low or no access to stores that sell healthy food items[15-21] and have disproportionately high access to fast food restaurants.[22,23] Others have found that low income/minority areas have fewer recreational facilities[24-27] and more physical disorder, sidewalk unevenness and obstruction[28] when compared to white and/or higher income areas. These results are contrasted with at least one study that found no race or income-related associations with recreational facilities and conflicting results about relationships between race and income and parks.[29] There is also conflicting results from research conducted in Australian and British settings, but for the purposes of this research, we are assuming that urban development is different enough in those areas to limit this discussion to American settings.

Since we know that minority groups often have disproportionately higher rates of chronic diseases, possible inequities in the distribution of resources to counteract disease is of interest. It is possible that unequal distribution of resources directly contributes to health inequalities.[25] In addition, without local access to supermarkets and recreational areas, or reliable transportation to reach distant locations, interventions aimed at changing individual behaviors could be less effective. And while we cannot equate the presence of a store or a park with their use, a recent review of the built environment and healthy behaviors among African-American empirically established that the presence of supermarkets was consistently associated with better diets.[30]

In Chapter 2, I describe an analysis of the association between race/ethnicity and densities of multiple health-related resources including supermarkets, recreational facilities, parks, and nearby retail areas. For this analysis, I employed new analytical tools that allow a close approximation of real-world access to individual and collective resources, instead of the more traditional approach of examining a single type of resource. When certain areas and/or certain groups of people are systematically denied access to the resources that could support healthy behaviors, while at the same time subjected to more environmental barriers to healthy behaviors, it is plausible that differences in health outcomes could result. As a nation, we are beginning to understand the social and economic consequences of race/ethnic and socioeconomic differences in health outcomes. This type of research, with its focus on the quantification of a range of resources, could contribute to better understanding of health inequalities and improved effectiveness of interventions.

Links between resources and healthy behaviors

Since the publication of first Surgeon General report on physical activity and health in 1996,[31] there has been an explosion of research examining how our built environment may contribute to sedentary lifestyles. Walking is a common outcome examined in this research because it is a common form of physical activity, it is hypothesized to be proximal to environments, and data on walking length and frequency is easily gathered from people.[32] It can be measured in many ways, and is commonly reported as walking for any purpose or walking for some particular purpose like transport (or utilitarian walking) or exercise. Some studies also differentiate between walking enough to meet some sort of recommended level of exercise.

Various characteristics of the built environment have been found to be associated with walking. Some research has linked increased walking for transport with perceived difficulty of parking,[33] perceived access to destinations,[34] and scenery, sidewalks, traffic, and distance to trails.[35] Walking at recommended levels or above has been associated with social cohesion and open space access,[36] and well-maintained sidewalks and knowledge of local routes.[37] Older women who live within walking distance to destinations were found to walk more.[38] A 2003 review of urban planning research found that walking was more common in areas with higher density, more connected streets, and a mix of land uses.[39] A follow-up review in 2008 found consistently positive associations between walking for transport and density, distance to destinations, mix of land uses, connectivity, open space, and safety.[40]

Another health behavior often linked to the built environment is diet, which is generally thought to be related to the environment through access to healthy foods at supermarkets. In addition to the collection of studies already referenced that document the gap in access to supermarkets in urban areas, additional research links supermarket access with dietary practices.[9,41,42]

Few, if any, studies consider how the clustering of resources in a particular area might predict the clustering of healthy behaviors like diet and exercise. Most of the literature examining the clustering of health behaviors is focused on identifying patterns of behavior clusters.[43-46] One study identified demographic predictors, such as age, higher level of education, and lack of depression or chronic disease, of health behavior clustering.[47] None of this research examined contextual factors, such as the clustering of health resources. The presence of multiple health resources could synergistically impact multiple behaviors through supporting and creating a culture of healthy behavior in a particular area. People may be more likely to adopt and maintain multiple healthier behaviors if they can access multiple resources.

In Chapter 3, I describe an analysis of how exposure to health resources, as captured by the Health Opportunities Score described in Chapter 2, is associated with exhibiting multiple healthy behaviors. The analysis is unique because it examines multiple resources and multiple behaviors, which created an opportunity to examine possible synergistic effects of multiple resources.

Examination of built environment measures

The sheer complexity of the relationship between the built environment and health might have contributed to conflicting findings in the literature and persistent questions about the best measures and methodologies to employ. For instance, one study found significant associations between physical activity and environmental factors like sidewalks, pleasant scenery and traffic vlume,[8] while another study found no significant impact of any single characteristic, including scenery and traffic.[48] A separate review of physical activity among African-Americans found mostly positive associations with light traffic, presence of sidewalks, and safety, but the actual strength of the association varied greatly and the findings were not consistent.[30] A recent review of 47 studies of the built environment and physical activity found some evidence that social support, connected trails, presence of physical activity equipment were associated with physical activity across multiple studies.[49] The same review notes that some of the inconsistent and null associations in the studies reviewed could be at least partly due to the fact that the environment is not an important predictor of behavior or that the environment is not being measured appropriately for the types of physical activity under review.

Another review of 18 studies of environmental influences on walking reached several conclusions about future research, including the need to develop reliable and valid measures of environmental attributes.[50] Environmental measurement in earlier studies generally exclusively relied on either perceived or objective measures, or treated the two types of measures as interchangeable if they appeared to address the same construct. More recent research suggests that the differences in results may be related to differences in how the two types of measures quantify environments. One study found more agreement between perceived and objective measures within smaller environments and among people with similar activity levels.[51] A recent review of links between crime and walking noted that studies with perceived crime measures found stronger links to walking than studies with objective measures.[52]

Differences in these findings could also be due to differences in the population under study, as there can be systematic differences in how people perceive the built environment and how they act on those perceptions. One study found that objective and perceived crime was associated with physical activity in girls, but not boys. [53] The same study found an association between proximity to open space and activity for boys, but not girls. Another study found that the effect of perceived neighborhood characteristics was mediated through individual-level attitudes and intention, which could hypothetically vary from population to population.[54] Further research is needed to more rigorously examine measures of the built environment.

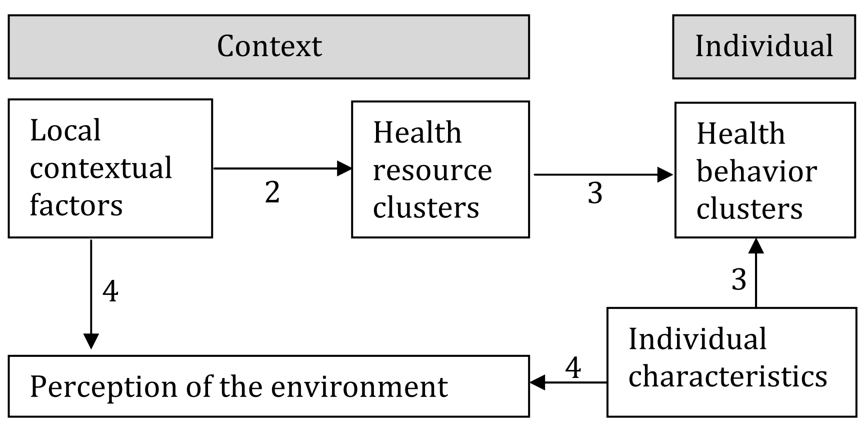
In Chapter 4, I describe a novel analysis that examines factors that predict perceived measures of the built environment and variation in perceptions within geographic units. I analyzed how local population density and median income, as well as individual demographic characteristics, were associated with variation in built environment perception. I believe this analysis is unique in its research question and approach, and yet it fits well in a field that is increasingly answer the call for greater examination of the rigor of its measurement tools.[11,12]

Conceptual Model

Some built environment research is explicitly guided by social ecological models of health behavior[55-57] or social determinants of health promotion.[13] The models tend to emphasize the same general constructs and conceive of health and healthy behaviors within a multi-level framework of influence, including individuals, clusters of individuals (like families), neighborhoods and other local areas, and macro-level environments with wide-ranging policies. All of these models recognize fluid movement between levels in all directions. For instance, individual behaviors are impacted by contextual and family characteristics, but those behaviors may also contribute to area context.

There have been recent calls for more,[4,58] or more clearly specified,[59] social ecological models to guide future research in this field. In order to understand the complex and cross-level nature of the constructs involved, clearer models must guide the research.[60] In response to this call, the following conceptual model guides this dissertation:

Figure 1.1 Conceptual Model



The model is based on the idea that the relationship between the built environment and healthy behaviors involves factors at both the contextual and the individual level. The model provides a simple overview of relationships between different factors that have been established or suggested by existing literature and are further examined in this dissertation. The model is not an all-encompassing illustration of the complex relationship between environment and health. Additional arrows and constructs could easily be added, but for the purposes of clarity, this model highlights constructs and relationships examined in this dissertation. The following description starts in the upper left corner of the model and moves through the model in a clockwise fashion.

Local contextual factors, such as area race and income, are thought to be associated with the clustering of health-related resources, a link that is supported by research that demonstrates that low income and minority areas have diminished access to single resources such as stores or recreational facilities.[14-22] Chapter 2 of this dissertation focuses on this link by first establishing the existence of resource clusters and then examining how area race/ethnicity is associated with resource clusters.

In turn, the clustering of resources is hypothesized to be associated with the clustering of health behaviors, such as exercising and eating a healthy diet. Resource clusters and behavior clusters are hypothesized to be associated with each other because existing research has consistently found relationships between individual resources and individual behaviors. Individual demographic characteristics, such as race/ethnicity, age, and sex, are also included in the model because they are strongly linked with healthy behaviors. Because different geographic areas may have different demographic profiles, it is imperative that an analysis of context and healthy behaviors, such as the one found in Chapter 3, account for individual characteristics.

These same individual demographic characteristics are known to be associated with individual perceptions of the built environment. After accounting for that association, it is hypothesized that contextual factors, such as median income and population density, may also be associated with the range of perceptions in a particular geographic area. This hypothesis, which could have implications for analytic methods in built environment research, is examined in Chapter 4.

Specific aims and hypotheses

Chapters 2-4 of this dissertation are each intended to be independent stand-alone manuscripts that examine the relationships illustrated in the conceptual diagram. The specific aim for each chapter, along with accompanying hypotheses, are listed below and summarized again, with results, in the concluding chapter of the dissertation.

Specific Aim 1 (Chapter 2): To quantitatively describe individual and collective spatial patterning of health-related resources (supermarkets, fresh food stores, recreational facilities, parks, and retail areas) by block group-level race in three distinct metropolitan areas.

Hypothesis 1: Block group race is associated with location of each individual health-related resource.

a. Block groups with more non-whites will have poorer spatial access to supermarkets and fresh food stores, recreational facilities, and retail areas.

b. Block groups with more non-whites will have better spatial access to parks.

Hypothesis 2: Health-related resources are clustered.

a. Block groups with low spatial access to any one resource are more likely to have low access to all other resources, except parks.

b. Block groups with high access to parks are more likely to have low access to other resources.

Hypothesis 3: Block groups with more non-whites will have poorer spatial access to clusters of health-related resources.

Specific Aim 2 (Chapter 3): Examine the association of clusters of health related resources, including densities of supermarkets, recreational facilities, and mixes of land uses (as assessed by a combined Health Opportunities Score), with the clustering healthy diet and physical activity behaviors.

Hypothesis 1: People with higher Health Opportunities Scores in their residential areas will be more likely than people with lower scores to demonstrate multiple healthy behaviors. In other words, the clustering of healthy diets and physical activity will be associated with living in an area with a higher HOS.

Hypothesis 2: The Health Opportunities Score will synergistically impact healthy behaviors above the level expected if the three components of the HOS were independently considered in a model.

Specific Aim 3 (Chapter 4): To improve measurement and understanding of the potential impact of the built environment by analyzing 1) the association between individual characteristics and perception and 2) variation in within-tract agreement on self-reported built environment measures in two diverse metropolitan settings.

Hypothesis 1: Individual demographic characteristics will be associated with perception of the built environment, but these associations will not account for all of the variation in perception seen within tracts.

Hypothesis 2: Within-tract agreement on self-reported measures will vary by the area-level demographic characteristics of population density and median income.

a. As population density and median income increase, variation in perceived aesthetic quality and perceived safety will decrease, because dense and wealthy tracts are likely to be less variable in aesthetic and safety features.

b. There will be less variation in walking environments in high and low density and income tracts, because these tracts are likely to contain uniformly positive or poor walking environments.

c. Perception of healthy food access will not vary by population density or median income.

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Chapter 2:

A spatial analysis of health-related resources in three diverse metropolitan areas

A growing body of public health research examines how health-related behaviors, such as diet and physical activity, are associated with features of the built environments in which people live, work, and play.[1-4] Specific health-related environmental features that are commonly investigated include the presence of supermarkets,[5-6] parks and recreational facilities,[7] and features related to the walkability of the environment, such as the presence of nearby destinations, connectedness of streets, and mixes of different land uses.[8-9] Studies have also shown that these types of features are spatially related to sociodemographic characteristics of the area, such as race and ethnicity. Previous research has found that areas with larger minority populations have stores with poorer quality produce,[10] low or no access to stores that sell healthy food,[5,6,11-15] disproportionately higher access to fast food restaurants,[16,17] and fewer recreational facilities.[18-20] This spatial inequality in health-related resources could be a contributing factor to racial and ethnic inequalities in health outcomes.

Parallel to this public health research, a body of research in urban planning examines patterning of area-level factors that are related to individual economic success. Historic residential racial segregation, along with a spatial distribution of jobs, affordable housing, and public transportation networks, greatly affects the ability of people to find and keep employment and housing. The spatial patterning of these types of factors creates a "geography of opportunity," such that individual economic success is associated with exposure to local opportunities.[21-22]

We hypothesize that just as the spatial clustering of jobs and housing define the geography of opportunity, the spatial clustering of health–related resources creates a "geography of health opportunity." In low health opportunity areas, the lack of multiple health-related features may have synergistic effects on health outcomes. Moreover, residents of these areas may be more likely to have individual-level disadvantages, creating the potential for even greater combined health effects. Understanding the geographic distribution and predictors of health opportunities, as well as their health consequences, could inform policy interventions.

To our knowledge, the collective spatial clustering of health-related resources and its association with area-level race/ethnicity has not been examined in U.S. settings. Previous research has examined these health-related resources separately[5,10,18] or in other countries such as Australia and England.[23,24] Because American development and residential patterns differ greatly from these other contexts, it is important to do this kind of analysis in American settings. We focused on multiple resources that have been linked to health-related behaviors: supermarkets and produce stores, parks and recreational facilities, and retail areas as walking destinations. Using data collected from three diverse American cities, we examined the spatial clustering of these resources in each city. In addition, in order to study how residential segregation was associated with the clustering of resources and health opportunities, we also investigated associations of health opportunities with the race/ethnic composition of the local and surrounding areas.

Methods

Three sites from the Multi-Ethnic Study of Atherosclerosis (MESA) Neighborhood Study are the focus of this analysis – Baltimore, MD (737 block groups in the metropolitan area), New York City, NY (819 block groups in Northern Manhattan and the Bronx), and Winston-Salem, NC (169 block groups in the metropolitan area). These analyses examined race/ethnic data from the 2000 US Census and densities of four health-related resources, the locations of which were collected for the MESA Neighborhood Study: 1) supermarkets/ produce stores; 2) recreational facilities; 3) parks; and 4) retail areas. These resources were selected because they commonly appear in the literature and have been linked to healthy behaviors. The number of block groups analyzed at each site was the contiguous area for which we could obtain locations of health-related resources, after accounting for the 0.5 mile buffer described below.

Information on locations and types of food stores was purchased in 2003 from InfoUSA (Papillion, Nebraska), a proprietary information service. Supermarkets were identified by selecting stores with recognizable chain name or more than 50 employees from all stores with Standard Industrial Classification (SIC) codes 541101 and 541104–541106. Produce markets were defined by SIC code (543101–543103, 549933). This analysis considered these two store types as a single type of resource likely to offer a variety of healthy foods. The decision to examine supermarkets and produce markets is supported by previous research suggesting a link between the presence of these types of stores and healthy dietary practices.[18]

Recreational facility and park data were collected between April 2003 and June 2004 using a combination of online searches, phone calls verifying and collecting resources, and reviewing information published by planning and park authorities. The data included street address, whether the facility was publicly accessible, and if a fee was associated with use. The type and quantity of physical activities available were also collected, with a total of 48 types of unique activities were identified.[7] Though these data were collected together, recreational facilities and parks are hypothesized to be patterned differently in space and are therefore treated as separate resources in this analysis.

The final health-related resource examined was retail area, which has been shown to be associated with walking trips.[25] Retail areas were identified from parcel-based land use and zoning data acquired from local planning authorities. The level of detail across sites varied greatly, as zoning codes in some sites broke down the general category of "retail" into numerous smaller categories. For this analysis, we collapsed categories of retail into a single general category that is comparable across all three sites. Because the distinction between current and planned land use was not always clear, all parcels zoned for retail use were considered retail.

Densities of all four health-related resources were estimated with a fixed kernel smoothing method, allowing for measurement of continuous resource densities over the entire area of each site.[26] Kernel estimation gives more weight to resources that are near each focal location, while allowing all resources within a given radius to exert some influence. We estimated resource densities within 0.5 miles of all 100m x100m grid cells inside the study areas. Cell-level densities were averaged to the block group level to obtain a summary measure of density for each block group. This approach of averaging densities for all cells over a given geographic area to provide an estimate of geographic accessibility of resources for definable spatial units has been used in numerous previous studies.[27,28]

These densities are not limited by block group boundaries, but instead reflect the range of resources reachable beyond the boundaries. In order to avoid boundary problems, we analyzed only block groups for which we had data coverage for at least 0.5 miles beyond their boundaries. We chose a 0.5 mile radius because it is small enough to limit the analysis to resources within a reasonable walking distance and large enough to likely include a selection of resources in each of our widely varied sites. We used straight-line distance, instead of network distance, because the quality of road network data (necessary to calculate network distances) varied by site and would have limited site comparisons.

Because population density affects resource density, we analyzed both raw densities of resources per square mile and "population density-adjusted" densities of resources per 10,000 people. To adjust for population density we divided the raw resource density kernel by a separate population density kernel and averaged the cell scores to the block group level. Additionally, park and recreational facility densities were weighted by the number of activities available, such that living near a park with more activities resulted in a higher park density as compared to living near a park that offered no activities. In the case of parks, activities available were assumed to be spread out evenly over the area of the park.

All analyses were site-specific. We calculated resource counts and block-group level densities (raw and population-density adjusted). We quantified spatial clustering of resource densities with Pearson correlation coefficients, after transforming mean densities into standard deviation units. Spatial autocorrelation of block group level densities was quantified with the Moran's I statistic. This statistic was calculated on raw resource densities and on residuals from univariate standard regression models with resource densities as a function of area level race/ethnicity. For these Moran's I calculations and all subsequent spatial regression models, we employed a queen's first-order weight matrix, which treats all block groups that share a border as neighbors.

We examined the association of resources with area race/ethnicity in two ways. Each block group was classified according to whether it was in the lowest site-specific quartile (low resource density) for zero, one, or two or more resource densities. We then calculated the percentage of people of each race/ethnicity who live in block groups with low spatial access to zero, one, or two or more resources. These analyses included only three resources (supermarkets/produce stores, recreational facility activities, retail areas) because the park activity density was not strongly correlated with the other resources. A separate category for Hispanic people was not analyzed in sites other than New York City because of the small Hispanic population in those sites.

Second, we examined associations of area race/ethnic composition with resource densities with traditional and spatial regression models using GeoDa.[29] Two types of spatial regression models (spatial lag and spatial error) were used in the analysis because of high spatial autocorrelation in the residuals of the standard models. In the spatial lag model, the outcome is modeled as a function of the independent variable (x_i) and weighted neighboring values of the dependent variable ($\rho w_i y_i$).

$$y_i = \beta_0 + \beta_1 x_i + \rho w_i y_i + \varepsilon_i$$

In this analysis, block-group level resource densities were modeled as a function of block-group race and densities of health-related resources in neighboring block groups. The dependent variable (y_i) was either a single resource density or a combination of multiple resource densities. The independent variable (x_i) was block group percent black (and additionally percent Hispanic in New York City). The β_1 coefficient was interpreted as the association of race/ethnic composition with resource density after controlling for neighboring block group resource density. Rho (ρ) captures the association of neighboring and local block group resources and therefore accounts for the spatial autocorrelation in the independent variable. The use of an interpretable spatial lag term (ρ) treats spatial autocorrelation as a phenomenon of interest. Significantly positive spatial lag terms indicate that local areas with high dependent variable values have neighbors with high dependent variable values.

In the spatial error model, spatial autocorrelation is treated as a confounder rather than a phenomenon of interest. The model has separate error terms for the spatially uncorrelated errors (ε_i) and for spatially correlated errors ($\lambda w_i \xi_i$). The parameter λ describes the extent to which the errors are correlated with each other, given the weighting scheme w_i. The beta coefficients are interpreted the same way.

$$y_i = \beta_0 + \beta_1 x_i + \lambda w_i \xi_i + \varepsilon_i$$

We contrasted both spatial models because both have some theoretical justification in our research problem. It is reasonable to expect that some portion of resource density is a function of neighboring area characteristics, suggesting that the spatial lag model that incorporates surrounding block-group densities as a predictor would appropriately capture the key underlying spatial processes. But it is also true that some of the spatial autocorrelation was introduced by calculation of the kernel densities themselves, suggesting a spatial error model to treat autocorrelation as a nuisance. Since the impact of surrounding areas on the local area is of scientific interest, but it is also partially due to spatial dependencies introduced by our methods, we report results from both types of spatial regression models.

The contextual effects of local block-group race/ethnicity and neighboring block-group race/ethnicity were calculated using different independent variables in two sets of models. In the first set of models, the independent variable was local-area (i.e., block group) percent black and in New York City we also included percent Hispanic. In the second set of models, the independent variable was the average of the local block-group racial composition and the racial composition of neighboring block groups (those sharing a border with the local block group). High correlations between local and surrounding block group race/ethnicity precluded including them as separate covariates in the same model, hence the weighted average was used as a single term. Comparison of the local-area versus local and neighborhood averaged models allowed us to assess the importance of features of both local and surrounding areas in shaping health opportunity patterns.

After modeling the association of race/ethnicity with each individual resource, we combined three individual resource densities (supermarkets/produce stores, recreational facility activities, retail areas) a measure of health opportunity called the Health Opportunity Score (HOS) and modeled it as a function of area race/ethnicity. In the absence of empirical data on the relative importance of each resource for health, we opted to scale each resource-density score to the same 1-100 range and combine them with equal weighting.

Results

Table 2.1 shows selected characteristics by site. New York City was the smallest site by land area, but the largest site by population. New York City had more health-related resources than the other sites except for retail area, which was more plentiful in Baltimore. As a result of high resource counts and small area, raw resource densities per square mile were highest in New York City. For example, there were 9.9 supermarkets/ produce markets per square mile in New York City, compared to 1.0 in Baltimore and 0.3 in Winston-Salem. New York City had 383 100-square meter retail areas per square mile, compared to 25.0 in Baltimore and 1.0 in Winston-Salem. There were 26.9 recreational facility activities per square mile in New York City, compared to 3.3 in Baltimore and 3.2 in Winston-Salem. Similarly, there were 31.6 park activities per square mile in New York City, compared to 5.1 in Baltimore and 3.3 in Winston-Salem.

After adjustment for population density, Winston-Salem had more supermarkets/produce markets (51.1 per 10,000 people), retail areas (200), recreational facilities (455), and park activities (435) than New York City or Baltimore. Baltimore consistently had the fewest resources per 10,000 people. Because availability of resources is often correlated with population density, and because there were no stark differences between regression models using unadjusted or adjusted resource densities, we report the results from models with population density-adjusted resource densities.

Pearson's correlation coefficients comparing population-density adjusted resource densities were mostly positive across all three sites, though they ranged from -0.03 to 0.62 (Table 2.2). The highest correlation was observed for retail area and recreational facility activities in Baltimore (r=0.62) and no correlation at all was observed for park activities and retail area in Baltimore (r=0.00). Most correlations were statistically significant at the $p<0.01$ level, with the exception of park activity density, which was not significantly correlated with any other density except recreational facility activities in Winston-Salem. Because our interest was in spatial clustering of resources, and because park density appeared to have a very different spatial pattern from the other resources, parks were omitted from further analyses.

With the exception of supermarket/produce stores and retail densities in Winston-Salem, residuals from standard linear regression models revealed statistically significant spatial autocorrelation (Table 2.2). For all resources, spatial autocorrelation in the residuals was consistently highest in New York City (Moran's I range from 0.76 to 0.92), intermediate in Baltimore (0.06 to 0.32) and lowest in Winston-Salem (0.01 to 0.24). The highest spatial correlation was observed for retail areas in New York City (0.92) and the lowest was observed for retail areas in Winston Salem (0.01).

In each site, more blacks than whites reside in block groups with two or three low resource densities (36% vs 19% in Baltimore, 28% vs 23% in Winston-Salem, 31% vs 12% in New York City). More whites, as compared to blacks, reside in block groups without any low resource densities (45% vs 35%, 37% vs 30%, 58% vs 28%). Hispanics in New York City showed similar patterns to blacks (Figure 2.1).

The low Moran's I statistics for Baltimore and Winston-Salem spatial model residuals indicated that nearly all of the spatial autocorrelation in the resource densities was accounted for (Tables 2.3 and 2.4). Results for spatial error and spatial lag models were generally similar. In Baltimore and Winston-Salem, higher local black population was associated with lower population density-adjusted supermarket/produce store, retail area, and recreational facility activity densities. The differences were statistically significant only for retail areas (in spatial lag models mean difference of -57.3 retail areas per 10,000 people [95% Confidence Interval -87.0,-27.6] for each 1% increase in black population), recreational facilities activities (-13.3 per 10,000 people [-21.4,-5.2]), and the summary HOS (-9.6 per 10,000 people [-14.3,-5.0]) in Baltimore and supermarkets/produce stores (-55.4 per 10,000 people [-104,-6.5]) and health opportunities (-633 per 10,000 people [-1221,-46.3]) in Winston-Salem. Spatial lag terms were statistically significant in all models except supermarkets/produce store density in Winston-Salem (in the spatial lag model). For all model types and health resources, except recreational facility activity density in Winston-Salem, associations were stronger when we modeled the average of the local and neighboring area race/ethnicity as the independent variable, as compared to models with only local race/ethnicity. The statistical significance did not change.

In contrast with Baltimore and Winston-Salem models, the relatively high Moran's I statistics in the New York City models suggest residual spatial autocorrelation, so results must be interpreted with caution (Table 2.5). In the spatial lag models, larger % black population at the block group level was generally associated with lower resource densities, although the relationship was only statistically significant for supermarkets/produce stores (-3.0 stores per 10,000 people [-4.9,-1.1] in spatial lag model). The spatial error model showed associations in a similar direction with the exception of recreational facility activities, which were positively rather than negatively associated with percent black, although confidence intervals for both model types were wide. In general, inverse associations were stronger for the spatial error models than the spatial lag models. The relationship between Hispanic population and resource density was less clear. In the spatial lag models, recreational facility activity density was inversely associated with local percent Hispanic (-8.6 per 10,000 people [-14.0,-3.2]) and local/surrounding percent Hispanic (-10.2 [-16.1, -4.2]), but no associations were observed in the corresponding spatial error models. In New York City, no consistent differences emerged when comparing models with only local race/ethnicity to those with local and neighboring race/ethnicity.

Discussion

Overall, our results from three diverse U.S. cities show that health-related resources are not randomly distributed across space. There was evidence of significant spatial clustering of resources, although the strength of this clustering varied across sites and resources. Three of the four resource densities (supermarkets/produce stores, retail areas, and recreational facilities) tended to be correlated with each other, whereas park activity density was less consistently and sometimes negatively correlated with the others. There was also evidence of a spatial association between resources and area race/ethnic composition: in all three sites, blacks were more likely to live in block groups with multiple low resource densities. In Baltimore and Winston-Salem, spatial regression models showed that block groups with higher proportions of black residents tended to have lower supermarkets/produce, retail, and recreational facility densities, although these associations did not always achieve statistical significance. A measure that combined local and neighboring block group racial composition was a stronger predictor of resources than the local measure in these two sites. Results for New York City were generally consistent but more variable, possibly due to stronger spatial clustering of resources. In contrast to results for black residents, the percent of Hispanic residents was not consistently associated with resource density in New York City.

The preponderance of research on health-related features of the built environment has found that single resource types such as supermarkets[5,10] or parks and recreational facilities[7,18,30] are unequally distributed in space, with fewer resources found in minority neighborhoods. Our results showed clustering of three resources in space, resulting in important geographic differences in multiple resources simultaneously. Parks, however, did not follow the same pattern. This may be related to the historical evolution of residential segregation at the sites we studied, whereby both resource rich and resource poor areas are located adjacent to parks. It is important to note that we examined only park activity locations, not the quality of parks. It is plausible that park quality is patterned similarly to other resources, even if park location is not. Other research has suggested that park quality differs in low income and minority areas, even when park area does not.[31]

We found that more blacks and Hispanics live in areas with more low resource densities as compared to whites. The results from our regression models also showed that densities of supermarkets/produce stores, retail areas, and recreational facility activities were associated with area race/ethnicity, although the strength and significance of these associations varied by site. Overall, these results are consistent with other work investigating associations of race/ethnic composition with each of the resources individually.[5,6,10-13,18-20] We added to this work by showing that similar patterns are present for multiple resource measures, and that minority areas are more likely to be disadvantaged in multiple resources, as observed in Figure 1. In addition, we also showed that these associations are not invariant, as illustrated by differences in the magnitude and direction of associations of resources with percent black and percent Hispanic in New York City.

We also investigated associations with a summary measure of health opportunities. In each site there was evidence that this summary score was often more strongly associated with race/ethnic composition than single resource scores. In both Baltimore and Winston-Salem, block groups with a greater percentage of black residents had significantly lower HOS, even when individual resources densities were not significantly different. In addition, at all three sites, clear differences across areas emerged when disadvantage across multiple resources was considered. If multiple resources act synergistically to affect health, the clustering of multiple types of disadvantage in space could have important implications for health inequities. Future attempts at quantifying health opportunities should examine multiple resources and may need to examine different weighting schemes for combining resource densities. Ideally, these weights should be based on the relative importance of different types of resources for health.

This analysis also provides some evidence that a combination of local and neighboring area characteristics could be a better predictor of health-related resource densities than local characteristics alone. In nearly every model in each site, the magnitude of the association between race/ethnicity and spatial access to resources was stronger when the surrounding area was included. These results suggest that highly segregated areas (i.e., areas surrounded by other segregated areas) are most likely to lack resources. This finding suggests future research may need to consider the impact of more than just local contextual factors.

A strength of this analysis is the examination of the clustering of disadvantage in multiple resources. The use of kernel densities to characterize resources available allows a more flexible and realistic representation of proximity to resources (by giving some weight to resources located in a buffer around block group borders) than the calculation of simple densities for geographic units. Other researchers are utilizing similar methods and calling for further investigations into access to multiple resources.[23] An additional strength is the use of two types of spatial regression models to account for spatial dependencies in the data. Though we only report results from models with queen's first order contiguity weights, we also ran models with three other weighting schemes and found no difference in the results. Spatial autocorrelation is a constant threat to the validity of spatial analyses and our use of kernel densities likely introduced additional spatial autocorrelation. The use of spatial regression models was appropriate in two sites, but residual spatial autocorrelation in New York City suggests the scale of the relationships is finer than we can resolve with this analysis. Future analyses may benefit from the use of site-specific buffer sizes or adaptive kernel sizes that are small enough to capture spatial differences in built environments and flexible enough to reduce variance in the densities.[26]

A limitation of this analysis is that it relies heavily on resource location and not more detailed measurements of resource quality. The inclusion of only large chain supermarkets and the weighting of recreational facilities and parks by number of activities on site, were attempts to account for resource quality but additional steps could be taken in the future with richer datasets. Additionally, the use of retail zoning land-use data as a proxy for local walkable destinations may mean that we included undesirable or empty retail areas. Therefore, while these results illustrate resources that may be considered accessible in a spatial sense, there may be numerous other barriers preventing local people from accessing and using them. Other factors, such as crime and safety, may be more relevant than the location of resources in shaping resource use and healthy behaviors.

This Health Opportunities Score treats each of the three component resources with equal importance. Some previous work has ranked resources according to their value for specifically defined populations[24] and future work should move in this direction, as empirical data of the relative value of different types of resources for different populations or outcomes becomes available. Our health opportunities summary measure is therefore an important starting point, but certainly not a complete or comprehensive measure of all local features potentially relevant to health.

Our sites were also not selected to be representative of the general population and future analyses should examine how resources cluster in other contexts and within geographic units other than block groups. In the absence of theory or empirical data linking a particular buffer size and health effects, we chose 0.5 mile buffers as a plausibly uniform walkable distance across three very different sites. Future refinements of our approach may include tailoring the buffer densities based on their importance to resource use and healthy behaviors. These analyses may also benefit from employing network rather than straight-line distances for constructing densities, as well as consideration of barriers to movement such as highways or bodies of water.

The absence of many health-related resources could have potentially synergistic effects on the residents of an area. Future work needs to more closely examine the clustering of these and other health-related resources, and then attempt to link these patterns to health behaviors and outcomes. These analyses may need to take into account numerous other factors that may modify the impact of resources such as social environment features (e.g. crime rates, perception of safety, social cohesion etc.) as well as cost and quality of resources.

Despite some limitations in the resource measures, our results clearly demonstrate that resources are not randomly distributed across space and that disadvantage in multiple resources cluster with local and surrounding area race/ethnic characteristics. These results highlight the importance of addressing these resource differences in order to reduce disparities in behaviors and other outcomes linked to resources.

Table 2.1: Selected area and resource characteristics by site

		Baltimore	Winston-Salem	New York City
Demographics	Area in square miles	158.3	208.5	16.4
	Block groups	737	169	815
	Population	818,501	245,028	1,405,255
	Black	53.1%	29.2%	24.0%
	Hispanic	1.9%	7.2%	45.5%
Counts[a]	Supermarkets	69	35	73
	Produce stores	17	4	80
	Retail area in square miles	18.9	0.7	1.1
	Recreational facilities	142	98	152
	Parks	132	67	119
Densities[b]	Supermarkets/produce stores	1.0/1.1	0.3/51.1	9.9/31.3
	Retail areas of 100 sq meters	25.0/61.6	1.0/200	383/1304
	Recreational facility activities	3.3/7.4	3.2/455	26.9/84.3
	Park activities	5.1/5.9	3.3/435	31.6/122
	Health Opportunities[c]	5.0/8.7	5.0/801	20.4/65.5

[a] The counts include total resources located within the final set of block groups analyzed. The count of resources analyzed is slightly larger than the counts reported here, because the analysis is based on all resources within ½ mile buffer of the analysis area.

[b] Resource densities are based on kernels with 0.5 mile radius. Mean block group densities are reported per square mile / per 10,000 people.

[c] Health Opportunities were created by scaling and equally combining supermarkets/produce store, retail area, and recreational facility activity densities.

Table 2.2: Pearson correlations between block group population-density adjusted resource densities and spatial autocorrelation for each density by site.

		Pearson's Correlation Coefficients[a]			Moran's I[b]
		Retail area	Rec facility activities	Park activities	
Baltimore	Supermarket/ produce store	**0.50	*0.09	-0.01	**0.17
	Retail area	--	**0.62	-0.01	**0.32
	Recreational facility activities	--	--	0.00	**0.06
	Park activities	--	--	--	**0.19
Winston-Salem	Supermarket/ produce store	*0.18	**0.20	0.01	0.08
	Retail area	--	0.13	0.04	0.01
	Recreational facility activities	--	--	**0.55	**0.24
	Park activities	--	--	--	**0.17
New York City	Supermarket/ produce store	**0.26	**0.45	-0.03	**0.83
	Retail area	--	**0.26	0.01	**0.92
	Recreational facility activities	--	--	-0.03	**0.81
	Park activities	--	--	--	**0.76

[a] Correlation coefficients are based on comparisons of densities after standard deviation standardization.
[b] Moran's I statistics indicate spatial autocorrelation in the residuals of traditional linear models with race/ethnicity predicting resource densities. This version of the Moran's I is reported because GeoDa only assesses statistical significance of the Moran's I using model residuals and not the raw data.
* = p-value of <.05
** = p-value of <.01

Figure 2.1: Percent of residents by block-group level resource densities and by race/ethnicity

Table 2.3: Mean differences in resource densities associated with block-group race/ethnic composition and residual correlation from spatial lag and spatial error regression models for Baltimore

		Health Opportunities		Recreational facility activities		Retail areas of 100m^2		Supermarkets and produce stores	
	Spatial model type	Error	Lag	Error	Lag	Error	Lag	Error	Lag
Local Racial Context[a]	% Black [95% CI]	**-13.2 [-19.9,-6.6]	**-9.6 [-14.3,-5.0]	*-15.6 [-24.9,-6.2]	*-13.3 [-21.4,-5.2]	**-90.3 [-143,-37.2]	**-57.3 [-87.0,-27.6]	-0.5 [-1.2,0.2]	-0.4 [-0.9,0.1]
	ρ^c		**0.4		*0.2		**0.6		**0.4
	Moran's I[d]	0.00	0.00	0.00	0.00	-0.01	-0.01	0.00	0.00
Local + Neighbor Racial Context[b]	% Black [95% CI]	**-16.1 [-23.5,-8.8]	**-10.8 [-15.8,-5.7]	*-16.7 [-26.7,-6.6]	*-14.0 [-22.6,-5.3]	**-124 [-187,-61.9]	**-64.0 [-96.0, -32.0]	-0.7 [-1.5, 0.1]	-0.5 [-1.0,0.0]
	ρ^c		**0.4		*0.2		**0.6		**0.3
	Moran's I[d]	0.00	0.00	0.00	0.00	0.00	-0.01	0.00	0.00

[a] Local racial context is modeled with local percent black as the independent variable.
[b] Local + Neighbor Racial Context is modeled with an independent variable that incorporates local percent black and percent black in surrounding block groups.
[c] ρ = The spatial lag term representing the association of the weighted average of race in neighboring block groups on the outcome.
[d] These Moran's I statistics are calculated in GeoDa without assessing statistical significance.
* = p-value of <.05
** = p-value of <.01

Table 2.4: Mean differences in resource densities associated with block-group race/ethnic composition and residual correlation from spatial lag and spatial error regression models for Winston-Salem

		Health Opportunities		Recreational facility activities		Retail areas of 100m^2		Supermarkets and produce stores	
	Spatial model type	Error	Lag	Error	Lag	Error	Lag	Error	Lag
Local Racial Context[a]	% Black [95% CI]	*-807 [-1555,-58.7]	*-633 [-1221,-46.3]	-455 [-1200,291]	-247 [-707,212]	-135 [-354,83.8]	-133 [-351,84.7]	*-64.2 [-120,-8.4]	*-55.4 [-104,-6.5]
	ρ^c		*0.3		**0.6		0.0		0.2
	Moran's I[d]	0.01	0.01	0.04	0.04	0.00	0.00	0.00	0.00
Local + Neighbor Racial Context[b]	% Black [95% CI]	*-995 [-1893,-96.6]	*-722 [-1394,-49.5]	-537 [-1538,464]	-243 [-764,277]	-174 [-421,73.4]	-172 [-420,75.9]	*-76.2 [-141,-11.2]	*-63.3 [-119,-7.4]
	ρ^c		*0.3		**0.6		0.0		0.2
	Moran's I[d]	0.01	0.01	0.04	0.04	0.00	0.00	0.00	0.00

[a] Local racial context is modeled with local percent black as the independent variable.
[b] Local + Neighbor Racial Context is modeled with an independent variable that incorporates local percent black and percent black in surrounding block groups.
[c] ρ = The spatial lag term representing the association of the weighted average of race in neighboring block groups on the outcome.
[d] These Moran's I statistics are calculated in GeoDa without assessing statistical significance.
* = p-value of <.05
** = p-value of <.01

Table 2.5: Mean differences in resource densities associated with block-group race/ethnic composition and residual correlation from spatial lag and spatial error regression models for New York City

		Health Opportunities		Recreational facility activities		Retail areas of $100m^2$		Supermarkets and produce stores	
	Spatial model type	Error	Lag	Error	Lag	Error	Lag	Error	Lag
Local Racial Context[a]	% Black [95%CI]	-6.0 [-14.2,2.2]	-2.2 [-4.6,0.3]	6.8 [-12.5,26.1]	-1.8 [-7.6,2.9]	-109 [-263,45.5]	-9.1 [-54.1,35.9]	**-8.1 [-14.2,-1.1]	**-3.0 [-4.9,-1.1]
	% Hispanic [95%CI]	4.3 [-2.5,11.2]	-0.5 [-2.6,1.6]	3.4 [-12.7,19.6]	**-8.6 [-14.0,-3.2]	74.4 [-54.4,203]	25.0 [-14.4,64.4]	0.01 [-5.1,5.1]	-0.4 [-2.0,1.1]
	ρ^c		**1.0		**1.0		**1.0		**1.0
	Moran's I[d]	0.16	0.17	0.15	0.16	0.21	0.22	0.12	0.13
Local + Neighbor Racial Context[b]	% Black [95%CI]	*-21.8 [-39.1,-4.5]	-1.7 [-4.3,0.9]	12.5 [-28.7,53.8]	-2.0 [-8.0,4.1]	-306 [-634,21.2]	0.4 [-47.1,47.9]	**-26.7 [-39.1,-14.3]	**-2.8 [-4.8,-0.7]
	% Hispanic [95%CI]	8.2 [-5.9,22.4]	-1.1 [-3.3,1.1]	-2.0 [-35.7,31.7]	**-10.2 [-16.1,-4.2]	234 [-33.1,502]	18.3 [-23.3,59.9]	-3.9 [-14.1,6.3]	-0.6 [-2.3,1.0]
	ρ^c		**1.0		**1.0		**1.0		**1.0
	Moran's I[d]	0.16	0.17	0.15	0.16	0.21	0.22	0.12	0.13

[a] Local racial context is modeled with local percent black as the independent variable.
[b] Local + Neighbor Racial Context is modeled with an independent variable that incorporates local percent black and percent black in surrounding block groups.
[c] ρ = The spatial lag term representing the association of the weighted average of race in neighboring block groups on the outcome.
[d] These Moran's I statistics are calculated in GeoDa without assessing statistical significance.
* = p-value of <.05
** = p-value of <.01

References for Chapter 2

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Chapter 3:

Associations between multiple health-related resources and clusters of healthy behaviors in three metropolitan areas

Research that examines the impact of the environment on healthy behaviors has consistently found positive associations between the presence of health-related resources, such as supermarkets and recreational facilities, and the healthy behaviors of people who live near them.[1-4] A possible limitation of this research is that it typically examines the association between a single type of resource and a single behavior, such as supermarkets and diet, without considering how clusters of resources could be associated with individual behaviors and clusters of behaviors.

Additionally, there exists an extensive field of research into health behavior clustering, but most of this literature focuses on identifying patterns of positive or negative behavior clusters.[5-8] At least one study identified demographic predictors, such as age, higher level of education, and lack of depression or chronic disease, of health behavior clustering.[9] But few, if any, of these studies examine how contextual factors, such as the presence of one or more health-related resources, might be associated with behavior clusters.

In prior work, we created a Health Opportunities Score (HOS) to attempt to gather a more complete picture of the range of different health-related resources across different metropolitan areas.[10] The HOS was created by combining separate densities of supermarkets and fresh food stores, recreational facilities, and retail areas in Baltimore, MD, Winston-Salem, NC, and portions of New York City, NY. These three domains were investigated because they commonly appear in the literature and have been consistently linked to a range of healthy behaviors. In previous analyses, we found that block group racial composition was associated with the HOS and that black residents were more likely to live in areas with a lower HOS.[10]

This new analysis builds on that existing work by analyzing the association between the HOS and the individual-level clustering of healthy behaviors in the same three metropolitan areas. We hypothesized that people with higher Health Opportunities Scores (HOS) in the area around their home address will be more likely than people with lower scores to engage in multiple healthy behaviors. In other words, we hypothesized that the clustering of healthy behaviors would be associated with living in an area with a higher HOS. Additionally, we hypothesized that the simultaneous presence of multiple resources, which is captured in the HOS, synergistically impacts healthy behaviors above the level expected if the three components of the HOS were independently considered in a model.

The presence of multiple health-related resources could synergistically impact healthy behaviors through several plausible mechanisms. First, the presence of multiple resources, such as a grocery store and a recreational facility, could help create and maintain a culture of healthy behavior in a particular area. For instance, people who are able to make an improvement to their diet may also be particularly willing to improve their physical activity levels. The presence of multiple facilities may also provide more opportunities for people to witness other people eating healthy foods and exercising, which also could contribute to a healthier culture in a particular area. Without longitudinal data, it is also possible that associations between behavior and resource clusters are the result of people who engage in healthier behaviors relocating to areas with multiple resources or demanding the provision of those resources in areas that did not previously have them. None of these plausible mechanisms are mutually exclusive, as multiple explanations could simultaneously operate. The possibility of a synergistic relationship between resources and behaviors is compelling enough to motivate the research described below.

Methods

The Multi-Ethnic Study of Atherosclerosis (MESA) is a longitudinal study of cardiovascular risk factors and disease in adults aged 45-84 years.[11] Using population-based approaches, approximately 1,000 white and black participants were identified at each site at MESA baseline. The New York City site also included approximately 1,000 Hispanic participants. The MESA Neighborhood Study, an ancillary study to MESA, collected additional community and built environment information from three of the six MESA sites (Baltimore, MD, Forsyth County (Winston-Salem), NC, and portions of New York City, NY). This analysis combined health behavior information collected in the MESA baseline exam with the Health Opportunities Score (HOS), which was calculated with data collected for the Neighborhood Study. The final analysis sample (n= 2,224) included all MESA participants from the three Neighborhood Study sites who consented to the neighborhood analysis and excluded those who provided incomplete diet (n=325), physical activity (n=3), demographic data (n=3), and whose address could not be accurately geocoded (n=16).

The outcome variable of interest in this analysis was created from diet and physical activity information collected at baseline examinations of the MESA cohort, which took place between July 2000 and September 2002. The outcome is an ordinal variable that captures the number of health behaviors (0, 1, 2, or 3) for which the person is in the "healthiest behavior" category, defined as the healthiest third of the sample. The behaviors that make up the variable were healthy diet, intentional exercise, and walking for transport. These three behaviors were chosen because of their hypothesized relationship with HOS components, as described below.

Dietary practices were quantified with a 120-item food frequency questionnaire where participants were asked the frequency of servings in a typical week.[12] The relative healthiness of diets was quantified with an empirically-derived factor score of fat and processed meat consumption that has previously been found to be associated with local food availability,[1] markers of inflammation,[13] and leukocyte telomere length.[14] Though our measure of health-related resources included produce markets, we chose the fat and processed meets factor instead of the fruit and vegetable consumption factor because the fat and meats factor has been linked to local food availability. Lower factor scores equate to healthier diets, so we considered participants in the lowest tertile of the factor score to have a healthy diet.

Physical activity information was collected by identifying the time and frequency of different physical activities in a typical week of the past month. Items were adapted from the Cross-Cultural Activity Participation Study and they did not account for seasonal variations in exercise due to weather.[15] This analysis utilized two composite measures of physical activity behaviors, intentional exercise and walking for transport, that were developed and used in previous MESA research.[16] The measure of intentional exercise, which consisted of the sum of minutes spent walking for exercise, engaging in sports/dancing exercise, and engaging in conditioning exercise, was hypothesized to be related to the recreational facility component of the HOS. The measure of minutes spent walking for transport was hypothesized to be linked to the retail area component of the HOS. Prior to analysis, both measures were transformed from minutes into metabolic equivalent (MET)-hours/week by converting minutes to hours and multiplying by MET level.[17]

The HOS was created by combining kernel densities of three health related resources: supermarkets and produce stores, recreational facilities, and retail areas.[10] Supermarket and produce store locations and descriptions were purchased in 2003 from InfoUSA (Papillion, Nebraska), a proprietary information service. The timeframe covered by these data closely matches the timeframe for the health behavior data. Supermarkets were defined as having a Standard Industrial Classification (SIC) code of 541101 or 541104–541106 and either a recognizable chain name or more than 50 employees. Produce markets were defined as having a SIC code of 543101–543103 or 549933. For inclusion in the HOS, a single density of these two store types was created, as both types are likely to offer a variety of healthy foods. The decision to examine supermarkets and produce markets is supported by previous research suggesting a link between the presence of these types of stores and healthy dietary practices.[2]

Recreational facility locations and descriptions were collected between April 2003 and June 2004 using a combination of online searches, phone calls verifying and collecting resources, and reviewing information published by planning and park authorities. The type and quantity of physical activities available were also collected, with a total of 48 types of unique activities identified.[3] This allowed the density of recreational facilities to be weighted by the number of activities available, such that facilities with more available activities were weighted higher.

Retail areas, which have been shown to be associated with walking trips,[18] were identified from parcel-based land use and zoning data acquired from local planning authorities. The retail area density was calculated after collapsing all parcels with current retail-related zoning codes (regardless of actual present use) into a single category that was comparable across sites.

Resource densities were estimated for cells in a 100m x 100m grid using a fixed kernel smoothing method, which gives more weight to nearby resources, while allowing all resources within ½ mile to exert some influence.[19] The HOS was calculated by combining the three densities and calculating a single HOS for the ½ mile straight-line radius around each MESA neighborhood study participant's baseline home address. This approach of averaging densities for all cells over a given geographic area to provide an estimate of geographic accessibility of resources for definable spatial units has been previously used.[20]

We used straight-line distance, instead of network distance, because the quality of road network data (necessary to calculate network distances) varied by site and would have limited site comparisons. Because population density has a great impact on resource density, we adjusted all densities for population density by dividing the raw resource density kernel by a separate population density kernel. The HOS variable was categorized as low if it was zero (45% of the sample), medium if it was below the median score of the non-zeroes (28%) , and high if it was above the median score for the non-zeros (27%).

Demographic information, which included sex, age, race/ethnicity, educational attainment, and household income, was also provided by survey respondents and re-categorized for analysis. Race/ethnicity was grouped into three mutually exclusive categories: white non-Hispanic (or white) (42.5%), black non-Hispanic (or black) (42.0%), and Hispanic (15.5%). Educational attainment was collapsed into high school diploma or less (32.9%), some college or post-secondary training (28.5%), or a Bachelor's degree or higher (38.6%). Household income was grouped as less than $12,000 (8.2%), $12-25,000 (15.2%), $25-40,000 (29.6%), $40-75,000 (19.6%), and $75,000 or more (22.3%). Respondents who did not provide an income (5.0%) were grouped in an "unknown" category in order to maximize the sample size.

We first examined differences across health behavior categories and across HOS categories for key variables. Chi-square and ANOVA tests were performed to assess statistical significance of any differences observed. To test our first hypothesis of HOS predicting clustering of healthy behaviors, we ran ordinal logistic regression models with low HOS as the referent and dummy variables for medium and high HOS. We began with a proportional odds model and tested the proportional odds assumption. The model was run with and without controlling for demographic characteristics of sex, age, race/ethnicity, education, and income, which were entered into the model as dummy variables for each category.

$$\ln(\theta_j) = \alpha_j + \beta[\text{HOS Medium}] + \beta[\text{HOS High}] + \beta[\text{Demographics}]$$

In this model, $\ln(\theta_j)$ is interpreted as the log odds of observing the same level of health behavior or higher for each health behavior level (j). The unique intercept for each level of health behavior (j) is α_j. β[HOS Medium] is interpreted as the log odds of greater clustering of healthy behaviors associated living in a medium HOS area, as compared to a low HOS area. β[HOS High] is interpreted as the log odds of greater clustering of healthy behaviors associated with living in a high HOS area, as compared to a low HOS area. Similarly the coefficients for the demographic variables are interpreted as the log odds of greater clustering of health behaviors associated with that variable level, compared to the referent level.

To test the second hypothesis that the HOS captures a synergistic effect of multiple resources on healthy behaviors, we ran ordinal logistic regression models with dichotomous variables for each HOS component and included all demographic variables. HOS components were dichotomized by whether or not the resource density was zero. We inferred that groups of components were associated with odds of behavior clustering if there was statistical interaction on a multiplicative scale between their components as reflected by a positive and statistically significant coefficient for the interaction term.[21] For each HOS component grouping, we ran a model that included the main effects of all components and a dummy variable that indicated whether or not the grouping was present.

Model 1: $\ln(\theta_j) = \alpha_j + \beta[\text{Supermarkets}] + \beta[\text{Rec facilities}] + \beta[\text{Retail}] + \beta[\text{Demographic}]$
Model 2: Model 1 + dummy variable for supermarket/rec facility
Model 3: Model 1 + dummy variable for supermarket/land use mix
Model 4: Model 1 + dummy variable for rec facility/land use mix
Model 5: Model 1 + dummy variable for supermarkets/rec facilities/land use mix

The statistical significance of the latter term indicated whether that combination of factors predicted behavior above and beyond the separate impact of the factors. For example, a positive, statistically significant interaction term indicated that the predicted value of the behavior odds was greater than what would be expected from the presence of each of the components separately.

Results

Of the final sample of 2,224 people, 130 (6%) people in the healthiest group for all three health-related behaviors, 503 (23%) were in the two behavior group, 798 (36%) were in the one behavior group, and 793 (36%) were not in the top third for any healthy behavior (Table 3.1). The behavior cluster groups differed in median HOS (p-value 0.05), which ranged from 0 in the zero behavior group to 30.2 in the three behavior group. Differences in the race/ethnic distribution across the behavior cluster groups were statistically significant (p-value <0.001). Black participants were overrepresented in the zero behavior group (46.4%) compared to the three-behavior group (33.9%) Hispanics were overrepresented in the 1-3 healthy behavior groups (19-20%) compared to the 0 healthy behavior group (7.9%). The groups also differed by site (<0.001), with more Winston-Salem residents in the zero behavior group (43.3%) and more New York City residents in the three-behavior group (47.7%). The behavior cluster groups did not differ significantly by sex (p-value 0.08), median age (0.78), or highest level of education completed (0.09).

Because the HOS was unevenly distributed in this sample, three uneven categories of HOS were used. The low HOS group contained everyone with an HOS of zero (n=1001 or 45%), while the middle (n=612 or 28%) and high (n=611 or 27%) HOS groups split the remaining portion of the sample at the median (Table 3.2). The distribution of health behaviors differed across HOS categories (p<0.001), as more people in the low HOS group demonstrated zero (41.8%) or one healthy behavior (35.9%), as compared to two (19.0%) and three (3.8%) behaviors. This distribution shifted for the high HOS group, where more people demonstrated three (7.5%) or two behaviors (27.5%) and fewer people demonstrated one (34.2%) or none (30.7%). HOS categories differed by race (p<0.001), due mainly to higher HOS in the Hispanic population. HOS categories also differed significantly by education (<0.001), as low (38.6%) and high (38.3) HOS areas had more people with Bachelor's degrees, whereas more people with high school diplomas or less lived in medium HOS areas (43.5%). Wealthier participants tended to live in lower HOS areas (p<0.001). Site was also associated with HOS (p<0.001), as low HOS areas had more Baltimore (42.8%) and Winston-Salem residents (56.1%) , medium HOS areas had more Baltimore (46.9%) and New York (53.1%) residents, and high HOS areas had more Winston-Salem (35.7%) and New York (61.5%) residents. The HOS categories did not differ by sex (0.16) or median age (0.24).

Table 3.3 shows odds ratios of healthy behaviors associated with the HOS categories before and after adjustment for covariates. Because the chi-square statistic from the unadjusted model was not statistically significant (p-value 0.39, not shown in table), we did not reject the proportional odds assumption and used proportional odds models throughout the analysis. In the unadjusted model, the odds of increasing healthy behaviors are 60% higher in the medium HOS group and 73% higher in the high HOS group, as compared to the low HOS group as a referent. These differences are statistically significant at the $p<0.001$ level.

Though the strength of the association is somewhat attenuated, the statistical significance of this association is maintained after adjusting for demographic variables, as the odds of increasing healthy behaviors are 40% higher in the medium HOS group and 52% higher in the high HOS group, as compared to the lowest group. Other statistically significant positive odds of healthy behaviors are seen with Hispanic race ($p<0.001$) as compared to whites and some college (0.004) and college degrees (0.001) as compared to people with a high school diploma or less. All other demographic variables were not significant predictors of healthy behaviors, after adjusting for all demographic variables and HOS.

Table 3.4 shows parameter estimates from the interaction models. Our analysis of possible synergistic interactions between components of the HOS determined that the presence of two or three of the components demonstrated a synergistic effect on the clustering of healthy behaviors. The parameter estimate for the interaction between supermarkets and recreational facilities was 0.48 (p-value 0.02), which suggests that the presence of both of these resources synergistically affects clustering of healthy behaviors. Similarly, the supermarket and retail interaction parameter estimate was 0.61 (p-value 0.01). Only the recreational facility and retail interaction was not statistically significant (p-value 0.12). The parameter estimate for the three-way interaction between all HOS components was 0.63 (p-value <0.001, suggesting even greater synergism in the presence of all HOS components.

Discussion

Research on links between behavior and environment has consistently found positive associations between the presence of health-related resources and healthy behaviors. One of the most frequently studied resources, supermarkets with fresh produce and other healthy foods, has been found to be associated with better dietary practices by local residents.[1-2] Nearby recreational facilities have been linked to higher physical activity levels in local residents.[3-4] Utilitarian walking has been associated with nearby retail land uses.[18] In this analysis, we found that living in an area with a high Health Opportunities Score was associated with higher odds of healthy behaviors involving diet, physical activity, and walking. We also found evidence that this association is synergistic, as residence near multiple health-related resources was associated with healthy behaviors above and beyond the association with individual resources.

The Health Opportunity Score (HOS) was originally created to provide a more complete illustration of the density of multiple resources across Winston-Salem, NC, Baltimore MD, and portions of New York City, NY. Our idea for an HOS originated from the urban planning and social science notion that locations of housing and jobs, alongside other factors, collectively create "geographies of opportunity" that impact individual economic mobility.[22] Similarly, we think that the arrangement of multiple health-related resources has the potential to define a geography of health opportunity across a region. Some recent public health research has encouraged the use of a geographic opportunity framework to both explain and intervene on health disparities.[23]

We found that the clustering of three health behaviors (diet, intentional exercise, walking for transport) was significantly associated with the HOS after adjustment for race/ethnicity, sex, age, education, and income. We also found evidence of interacting effects between the HOS components and clustering of healthy behaviors, suggesting that the association between healthy behaviors and the HOS is due to more than just the effects of its component parts. People living in an area with more than one healthy resource appear to be even more likely to engage in healthy behaviors than people living in areas with one or no resources. As noted in the introduction, most analyses of health behavior clustering identify patterns of behavior clusters[5-8]or demographic predictors of health behavior clustering.[9] We believe this is one of the only studies to examine and find associations between contextual characteristics and behavior clustering.

Based on our results, the density of supermarkets and fresh food stores is most likely to be strongly related to behavior in its interaction with other components. This could be due to the stronger effect of supermarkets on behavior, if the availability of fresh food acts as a gateway to other healthy behaviors. Supermarket densities could also signal other characteristics of a neighborhood, such as safety or higher socioeconomic status, that are themselves related to behaviors.

Because site of residence was strongly associated with the HOS, we did not control for site in the model. Therefore, it is possible that some of the association between resources and behaviors is due to site-related confounding in the dataset. Future site-specific analyses, similar to those done in the first HOS paper,[10] could avoid this potential issue. We did not opt to do that at this time, as we believe that analyses of resource clusters are most useful when they are transferable across a variety of cities and types of development, and we currently do not have any evidence that the relationship between environment and behavior differs by city.

Other research in this field has also consistently found that low-income and minority areas have fewer health-related resources, poorer quality resources, and more barriers, such as safety, that diminish opportunities to utilize local health-related resources.[24-29] A separate line of research suggests that immigrant enclaves may be protective of some health behaviors.[30] Our analysis offers some support for that research, as we found that Hispanics were much more likely to demonstrate one or more healthy behaviors and live in a higher HOS area. In our sample (results not shown), roughly 2/3 of the Hispanics in our sample are in the healthiest diet category, which accounts for the small number of them in the zero behavior category. An earlier analysis that used a similar dataset also found similar results for Hispanics when using the fat and processed meat factor score.[2] The relationship between this measure of diet and this ethnic group may be a topic for future analyses. We also suspect that at least some of the reason for higher HOS in the Hispanic sub-group is due to the fact that they were disproportionately from the New York City site.

There are several limitations to both the exposure and outcome variables in this analysis. Our HOS quantifies resource densities within uniform ½ mile radii for each site. It is possible that the appropriate area for accessing health resources is a different size in New York City, as compared to Winston-Salem. We could find no empirical evidence supporting the use of different site-specific radii, but given the strong site-resource association, future analyses may reconsider this.

Additionally, the data used to calculate the resource densities does not include quality of the resources or any other barriers (such as cost, language, safety) that may prevent people from utilizing resources that are geographically close to them. We did select only large supermarkets and produce stores, to try to focus on stores that are likely to sell fresh food and we also adjusted the recreational facilities density for the number of activities available each facility. But we know there is room to improve the detail in that data, as additional information becomes available. Therefore, the HOS analyzed here represents the largest number of the type of resources we chose to analyze possibly available in our areas.

In addition to adding information on quality of resources, future iterations of the HOS could also include additional types of resources. In our original HOS analysis, we also considered including parks, and eventually left them out since park densities did not correlate with the densities of other resources. Additional resources that could plausibly be related to healthy behaviors, such as bike lanes and sidewalks, could be added to the HOS in the future.

Our outcome variable captures the clustering of healthy behaviors using variables that have been analyzed elsewhere,[2,13.16] but it is possible that different measures of these types of healthy behaviors could be differently linked to the HOS. In particular, the use of MET-min/week as the unit of measurement for the physical activity variables, without consideration of speed of walking, could have diminished the effectiveness of the physical activity measures. It is also possible that other healthy behaviors, in addition to those examined here, could have different clustering patterns in response to resource clustering.

Our finding of a synergistic association between clusters of health resources and behaviors is hypothesized to be due to the synergistic effect that the presence of multiple resources has on a local area. This finding could be explained by other mechanisms, including the relocation of people who engage in multiple healthy behaviors to areas with multiple resources. This finding could also be due to residual confounding by other contextual factors that are commonly found in high-resource areas, such as high area socio-economic status, that could also be associated with healthy behaviors. There are also interesting questions about possible temporal aspects to this analysis. Though our resource and behavior data were gathered for roughly the same time period, ideally the resource data would be gathered prior to the behavior data, to allow time for the impact of the resources to occur. Future analyses could take area factors or temporal factors into account.

This analysis examined how exposure to multiple health-related resources was associated with clustering of multiple healthy behaviors. We found a positive and synergistic association between resources and behaviors. If additional future analyses support this finding, it could suggest that the synergism relationship between resource and behavior clusters could be contributing to inequities in healthy behaviors and health outcomes. People who live in areas with few or no resources could be at an additional disadvantage when compared to people living in areas that are well-served by health-related resources.

In addition to possibly explaining some part of persistent gaps in health outcomes, the synergistic association could have important implications for interventions on the built environment. Initiatives that focus on provision of a single type of health resource, such as supermarkets, would be clearly benefit the area but they also may not be enough to single-handedly close those gaps. Comprehensive approaches to the creation and maintenance of a host of health resources in a particular area, such as supermarkets, recreational facilities, and walkable destinations, may be more effective in reducing persistent gaps in health outcomes. In situations where comprehensive approaches are not economically feasible, it may make sense to prioritize the addition of missing resources in areas that already have a few resources. If these findings are replicated in other studies, policy-makers may determine that maximizing the number of health resource clusters ultimately has the greatest impact on health inequities.

Table 3.1: Selected characteristics of study participants by number of behaviors in highest tertile

	Total Sample	Number of behaviors 0	1	2	3	p-value[a]
	n=2224	n=793	n=798	n=503	n=130	
% Female	53.6	53.1	52.6	52.9	64.6	0.08
Median age in years	63.0	62.0	62.0	63.0	65.0	0.78
Race						<0.001
White	42.5	45.7	38.7	42.2	46.9	
Black	42.0	46.4	42.2	37.0	33.9	
Hispanic	15.5	7.9	19.1	20.9	19.2	
Education						0.09
HS or less	32.9	34.4	34.7	29.8	24.6	
Some college/cert	28.5	28.9	26.6	31.0	28.5	
Bachelor or more	38.6	36.7	38.7	39.2	46.9	
Income						0.29
Less than $12,000	8.2	7.7	9.4	7.2	8.5	
$12-25,000	15.2	15.9	13.0	17.3	16.9	
$25-40,000	29.6	28.8	30.6	29.8	28.5	
$40-75,000	19.6	19.3	20.1	18.9	20.8	
$75,000 and more	22.3	22.1	21.4	23.9	23.1	
Unknown	5.0	6.3	5.5	3.0	2.3	
Site						<0.001
Baltimore, MD	32.9	38.2	30.0	30.0	30.0	
Winston-Salem, NC	35.1	43.3	35.6	24.7	22.3	
New York City, NY	32.0	18.5	34.5	45.3	47.7	
Median Health Opportunities Score	5.4	0	8.1	18.3	30.2	0.05

a – p-values demonstrate the statistical significance of Chi-square and ANOVA tests of differences observed across behavior categories

Table 3.2: Selected characteristics of study participants by Health Opportunities categories

	Total	Low HOS	Medium HOS	High HOS	p-value[a]
	n=2224	n=1001	n=612	n=611	
% Female	53.6	51.8	56.7	53.4	0.16
Median age in years	63.0	63.0	63.0	62.0	0.24
Race					<0.001
White	42.5	49.5	33.8	39.6	
Black	42.0	50.2	36.4	34.4	
Hispanic	15.5	0.4	29.7	26.0	
Education					<0.001
HS or less	32.9	26.2	43.5	33.4	
Some college/cert	28.5	29.0	28.0	28.3	
Bachelor or more	38.6	44.9	28.6	38.3	
Income					<0.001
Less than $12,000	8.2	4.1	14.7	8.5	
$12-25,000	15.2	12.0	17.3	18.5	
$25-40,000	29.6	25.4	34.0	32.2	
$40-75,000	19.6	22.7	17.8	16.2	
$75,000 and more	22.3	29.1	13.9	19.6	
Unknown	5.0	6.8	2.3	4.9	
Site					<0.001
Baltimore, MD	32.9	42.8	46.9	2.8	
Winston-Salem, NC	35.1	56.1	0.00	35.7	
New York City, NY	32.0	1.1	53.1	61.5	
Clustering of healthy behaviors					<0.001
0 behaviors	35.7	41.8	30.6	30.7	
1 behavior	35.9	35.5	38.3	34.2	
2 behaviors	22.6	19.0	23.7	27.5	
3 behaviors	5.9	3.8	7.5	7.5	

a – p-values demonstrate the statistical significance of Chi-square and ANOVA tests of differences observed across HOS categories

Table 3.3: Odds ratios of health behavior clustering associated with HOS categories before and after adjustment for covariates

Variable	OR estimate	95% Wald CL	p-value
	Unadjusted Model		
Low HOS	ref		
Medium HOS	1.60	1.33, 1.93	<0.001
High HOS	1.73	1.43, 2.08	<0.001
	Adjusted Model		
Low HOS	ref		
Medium HOS	1.40	1.15, 1.72	0.001
High HOS	1.52	1.25, 1.84	<0.001
Female	ref		
Male	0.88	0,75, 1.03	0.11
Age in years	1.01	0.99, 1.02	0.07
White	ref		
Black	1.00	0.84, 1.19	0.99
Hispanic	2.02	1.55, 2.63	<0.001
HS or less	ref		
Some college/cert	1.36	1.10, 1.67	0.004
Bachelor’s or more	1.48	1.20, 1.83	0.001
Less than $12,000	ref		
$12-25,000	1.15	0.82, 1.61	0.43
$25-40,000	1.19	0.87, 1.65	0.28
$40-75,000	1.28	0.90, 1.83	0.17
$75,000 and more	1.38	0.95, 1.99	0.09
Unknown income	0.86	0.55, 1.35	0.51

Table 3.4: Results from interaction models with HOS components predicting healthy behaviors

	Parameter Estimates (p-values)				
Variable	no interaction model	food / rec interaction model	food / retail interaction model	rec/retail interaction model	full interaction model
Supermarkets/ fresh food stores	0.40 (<0.001)	0.08 (0.63)	-0.09 (0.66)	0.38 (<0.001)	0.05 (0.72)
Recreational facilities	0.14 (0.15)	-0.02 (0.86)	0.13 (0.16)	-0.06 (0.72)	-0.04 (0.69)
Retail areas	0.24 (0.02)	0.25 (0.01)	0.12 (0.27)	0.12 (0.32)	0.16 (0.11)
food/rec interaction		0.48 (0.02)			
food/retail interaction			0.61 (0.01)		
rec/retail interaction				0.30 (0.12)	
Food/rec/retail interaction					0.63 (<0.001)

These models used dichotomous variables (zero vs. non-zero) for resource variables and controlled for demographic characteristics.

References for Chapter 3

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Chapter 4

Differences in environmental perception: Individual and contextual factors and possible implications for neighborhood research

The association between the built environment and human health and behaviors, such as physical activity,[1,2] diet,[3,4] mental health,[5] and obesity,[6-8] continues to be the subject of much research. Much of this research suggests that the built environment has great potential to influence human health, but persistent methodological concerns preclude the causal interpretation of many findings. Newer research addresses some of these methodological concerns, such as whether findings are due entirely to healthy people selecting into healthy environments,[9-11] how best to define neighborhood boundaries,[12,13] and how to avoid conditioning on mediating factors,[14] but considerable methodological questions require further exploration. A particular area of focus for new research involves a rigorous re-examination of how built environments are measured, as noted by two recent reviews of the state of built environment research.[15,16] Though each review focused on different types of measurement, both concluded that built environment health research would be improved by additional examination and improvement of all measures.

We define the built environment as all aspects of the environment that have been made by humans for human use. This broad definition, which has appeared in other research,[17] includes roads, retail stores, sidewalks, and most features of the every-day environment that people interact with. The built environment is commonly measured with surveys that ask people to rate the quality and/or presence of various features of the area in which they live. Within any neighborhood, census tract, or any other geographic unit, residents may perceive the environment differently from each other. For example, where one person might enjoy walking along a busy street, another person might perceive that same street to be loud or dangerous.

Traditional analytical methods minimize, or eliminate altogether, any variation in survey responses by aggregating responses from multiple people up to a common geographic unit, such as a census tract or block group. The aggregate score, which is essentially the "average" perception of an area, is assumed to describe the environment contained within that unit. Small differences in responses are eliminated by this process, which treats the differences like statistical noise to be eliminated in order for the "true" characteristics of an area to emerge.

This analysis began with the premise that differences in perception of the built environment might be meaningful, in terms of people's health and their interaction with the build environment, and not just nuisances to be eliminated prior to analysis. For example, two neighborhoods could each have the same aggregate rating of park facilities, but residents of one area could all have reported the same number, whereas residents of the other area could have reported extremely high and low ratings in equal numbers. Both of these neighborhoods would have the same aggregate rating, but the residents one neighborhood perceive the environment very differently from each other. Improvements to the parks in each of these neighborhoods could have very different effects human behavior, since people did not agree on the initial park quality.

We pose three possible explanations of variation in people's perception of the built environment. First, variation could reflect the range of individual-level characteristics in the area population. Neighborhoods containing residents with a range of ages, for instance, could have more varying perception of the environment as compared to areas with a more homogeneous population. Second, variation could be associated with some characteristic of the environment itself, such that certain types of environments lend themselves to more varied perceptions as compared to others. For instance, very densely developed areas could be more likely to be perceived differently by their residents, whereas rural areas could be perceived more uniformly. Third, variation could be a function of true environmental heterogeneity within geographic units. This explanation could be particularly relevant to tract-level analyses, since census tracts generally do not capture the boundaries of traditional neighborhoods, and run the risk of grouping very different places together into a single tract.

For this analysis, we decided to explore the second explanation above with multi-level modeling of how population density and median income were associated with variability in resident perceptions of aesthetic quality, safety, walkability, and healthy food access within New York City and Los Angeles census tracts. We hypothesized that as population density and median income increase, variation in perceived aesthetic quality and perceived safety would decrease, because dense and wealthy tracts are likely to be less variable in aesthetic and safety features. We expected to see less variation in walking environments in high and low density and income tracts, because these tracts are likely to contain uniformly positive or poor walking environments. In our review of the literature, we found no reason to believe that perception of healthy food access would vary based on population density or median income, so we included this scale as a specificity test of our theory.

Since the multi-level models controlled for individual demographic characteristics, we could eliminate the chance that any association found between context and variation was due to individual characteristics, which was our first suggested cause of variation in perception. The third suggested cause, the possibility of true environmental heterogeneity, could not be controlled for in this analysis. Therefore, it remains a competing explanation for our findings and this point is developed further in the conclusion.

Methods

This analysis uses data from Community Survey II, a study of social and built environment data that is ancillary to the Multi-Ethnic Study of Atherosclerosis (MESA), a multi-site longitudinal study of factors associated with atherosclerosis development. Community Survey II employed random digit dialing and listed household sampling frames to efficiently target areas where MESA participants lived. In total, there were 5,178 respondents in 628 census tracts in Los Angeles, CA and portions of New York City, NY. To allow for better investigation of within-tract variation in responses, we restricted this analysis to the 3,883 respondents who provided full demographic data in the 237 tracts with at least five respondents. Recent research suggest that including tracts with fewer than five respondents may limit the ability to detect contextual effects.[18]

The survey questionnaire focused on items that are relevant to cardiovascular disease development and respondents were asked to consider an area within approximately one mile of their home address. This analysis examined scales assessing aesthetic quality (five items), access to healthy foods (three items), safety (three items), and walking environment (seven items) that were developed based on existing research (Table 1).[19,20] All items were answered on a five-point Likert scale and were coded so higher scores indicate "better" neighborhoods (e.g., better aesthetics, higher perceived safety).

The analysis utilized three-level multi-level models to examine the relationship between variation in perception and the contextual variables of population density and median income.

Sample Model: $Y_{ijk} = \beta_0 + \beta_{1\text{-}5}x_{jk} + V_{0k} + U_{0jk} + e_{ijk}$

The outcome variables were survey scale items (i) that were nested within individuals (j) who were nested in tracts (k). Each model also contained individual race/ethnicity, age, sex, education, income and years spent in the neighborhood ($\beta_{1\text{-}6}x_{jk}$). We chose these variables because they have been shown to be associated with people's perception of the built environment,[21-24] so their inclusion allowed us to account for heterogeneity of individual-level characteristics in explaining contextual differences in within-tract variability.

The variance components in this multi-level model are: between-tract variance (T_k variance of V_{0k}), which capture departures from the overall tract-level mean, within-tract variance (T_j variance of U_{0jk}), which captures departure from the individual-level mean within tracts, and within-person variance (σ_2 or variance of e_{ijk}), which captures departures from individual mean scale scores. This portioning of variance components allowed us to examine changes in within-tract variance.

Three versions of the multi-level model were run for each built environment scale: a demographic variable-only model, a contextual main effect model, and a contextual stratified model. The variance components from the demographic variable-only model provided a baseline distribution of variance after accounting for individual factors. The contextual main effect model, which included demographic variables and a contextual variable (population density or median income), produced variance components that accounted for for individual variables and the main effect of the contextual variable. By definition, within-tract variance for these two models are the same, since the contextual factor is a tract level variable and all people in a single tract have the same value; hence the addition of contextual variables will not alter estimates of residual within-tract variance.

In order to allow the within- and between-tract variance to differ by context, the third version of the model was fully stratified by the three levels of the contextual variable. The stratification allows the variance components to differ by levels of the contextual variable, which allowed us to compare the amount of within-tract variance by levels of the contextual variable. Cut-offs for the stratification by contextual variables were identified by creating three equal-sized groups of census tracts that correspond to high, medium, and low density or income in the sample.

We assessed the impact of contextual variables on within-tract variance in perception by comparing the intraclass correlation coefficients (ICCs) from each model. The ICCs were calculated by dividing the between-tract variance by the sum of between-and within-tract variance and are interpreted as the proportion of total variance that lies between the tracts (as opposed to within the tracts). In other words, our hypotheses of more within-tract variation correspond to lower ICCs. To approximate the statistical significance of changes in ICCs, we conducted a likelihood ratio test comparing test statistics from main effects models with the sum of the test statistics from the stratified model. Because the fixed portion of the two models is the same, this comparison focuses solely on the effect of allowing the variances to differ by levels of the contextual variable.

Results

All of the built environment survey scales demonstrated relatively high internal consistency, with Chronbach's Alphas ranging from 0.75-0.78 (Table 4.1). Though we identified a sample of 3,883 respondents with complete demographic data, some respondents provided incomplete information on some scales. In order to maintain the largest possible sample, and also because we were not comparing across built environment constructs, the final sample for each scale consists of all respondents who provided complete data for that scale. The scale-specific sample sizes range from 3,668 for walking environment to 3,775 for aesthetic quality.

The overall sample is mostly white (36.4%) and Hispanic (35.0%), with whites disproportionately represented in low density and high income tracts (Table 4.2). 43.9% of the sample has at least a bachelor's degree, and these people are also more likely to be found in low density and high income tracts. 62.1% of the sample is female, the median age is 50 years, and respondents have lived a median of 13 years in their neighborhood. People in low density and high median income tracts tend to be older and have lived there longer. Each demographic variable is statistically significantly associated with population density or median income (p-value < 0.001) except for sex and population density (0.11) or median income (0.03). Though each site has roughly half of the census tracts in the sample, more of the Los Angeles tracts are low density, while more of the New York tracts are high density.

Mean built environment scale scores differed significantly (p<0.001) by categories of demographic variables and contextual variables (Table 4.3). Men have higher mean scale scores, but only the score for the safety scale (3.44) reaches statistical significance as compared to women (3.28). In general, whites and people who are wealthier and have more education report better scale scores. Scores in Los Angeles, as compared to New York, are significantly higher for aesthetic quality (3.68 vs 3.29), healthy food (3.51 vs 3.38), safety (3.46 vs 3.23), and significantly lower for walking environment (3.68 vs 3.72).

Built environment survey scales were all statistically significantly associated with the contextual variables at a p<0.001 level. On a scale of 1 ("worse" tract) to 5 ("better" tract), aesthetic quality had an average mean of 3.48 and was lowest in high density (3.20) and low income (3.10) tracts, as compared to low density (3.91) and high income (3.92) tracts. The average mean was 3.48 for healthy food access with lowest scores in high density (3.33) and low income (3.10) tracts. Mean perceived safety was 3.34, but the range from low (2.88) to high (3.90) income tracts was the largest gap. Walking environment had a mean score of 3.70 and was highest in low density (3.88) and high income (4.05) tracts.

From the multi-level models, the main effects of demographic and contextual variables on perception of the built environment scales are summarized in Table 4.4. After accounting for the clustered data and controlling for all other demographic variables, blacks reported higher aesthetic quality (mean scale score 0.18 points higher, p-value < 0.001), safety (0.09, p<.05), and walking environment (0.10, p<.05). Mean built environment scale scores generally dropped as education increased, but these decreases were only statistically significant for aesthetic quality (-0.06) and healthy food (-0.10) for people with some college, and healthy food (-0.11) for college graduates. The highest household income group reported higher aesthetic quality (0.12, p<.05), safety (0.14, p<.05), and walking environment (0.16, p<.001) than the lowest income group.

According to the models, the built environment scale scores were higher in low density and high income tracts, as compared to high density and low income tracts. For aesthetic quality, mean scores in low density tracts were 0.77 (p<.001) higher than in high density tracts and low income tract mean scores were 0.88 (p<.001) lower than in high income tracts. For healthy food access, low density tracts were 0.35 (p<.001) higher, while low income tracts were 0.80 (p<.001) lower. Safety mean scores were 0.68 (p<.001) higher in low density compared to high density tracts and 1.01 (p<.001) lower in low income as compared to high income tracts. Low density tracts had higher mean walking environment scores than high density tracts (0.25 p<.001), while low median income tracts had lower walking environment scores (-0.58 p<.001) as compared to high median income tracts.

The addition of population density to the models with only individual-level controls eliminated some between-tract variance and the ICC dropped from 0.48 to 0.31

(aesthetic quality), 0.27 to 0.25 (healthy food), 0.43 to 0.34 (safety) and 0.37 to 0.35 (walking environment). After stratification by population density, the lowest ICCs were consistently found in the high density tracts. For aesthetic quality, ICCs ranged from 0.42 (low density) to 0.28 (high density). For other models, the ICCs ranged from 0.28 to 0.26 (healthy food), 0.43 to 0.27 (safety) and 0.42 to 0.34 (walking environment).

With the addition of median income, the between-tract variance and thus the ICCs also dropped from 0.48 to 0.27 (aesthetic quality), 0.27 to 0.16 (healthy food), 0.43 to 0.23 (safety), and 0.37 to 0.24 (walking environment). After stratification by median income, the lowest ICCS were consistently found in the low income tracts. For aesthetic quality, ICCs ranged from 0.11 (low income) to 0.41 (high income). For other models, the ICCs ranged from 0.05 to 0.21 (healthy food), 0.09 to 0.33 (safety) and 0.17 to 0.32 (walking environment).

For all built environment scales, likelihood ratio statistical tests comparing the main effect model (with additional interaction terms for this test) with the stratified model indicate that the stratified model is a better fit at the $p<0.01$ level. The results of this test suggest that stratum-specific differences in the variances for each built environment scale are statistically significant.

Discussion

The body of research linking the built environment with human health and behavior continues to develop in size and complexity. The association between aspects of the built environment and physical activity,[1,2] diet,[3,4] mental health,[5] obesity,[6-8] and other health-related topics has been widely examined. Two recent reviews of the literature in this field call for closer examination of the tools we use to measure aspects of the built environment.[15,16] A tool that requires further exploration involves how the traditional analysis of data gleaned from resident surveys, a staple of built environment measurement, may ignore meaningful differences in resident perceptions.

Traditional analyses aggregate multiple survey responses up to a single geographic unit. This method assumes that the aggregate measure represents a true measure of the built environment and eliminates any possible variation in people's perceptions. Yet there exists a significant collection of research into meaningful differences in perception of the environment. Considerable research has established that there are sex-, age-, and race-related differences in perception.[21-24] A particular body of research into race-based differences in perception and preferences of racial make-up of neighborhoods has found that blacks prefer a higher degree of residential racial integration as compared to whites.[25,26] As noted in the introduction, this cause of variation was controlled for in this analysis by including individual demographic characteristics in the models.

Some existing research suggests that people living near each other have reasonably high levels of agreement about their environments.[19] Other work, however, suggests that both individual and contextual characteristics could differently impact people's perceptions of the walking environment[27] and racial discrimination.[28] The possibility that environmental context, in addition to individual characteristics, may be associated with variation in environmental perception has not been fully explored. This analysis examined how variation in the perception of the built environment was associated with the contextual variables of tract-level population density and median income. We chose these two contextual variables because they capture constructs that are closely related to how people experience environments. Previous work has suggested that there are urban, suburban, and rural differences in the association between the environment and physical activity,[29-31] so we hypothesized environmental perception could similarly differ by environment type, above and beyond the variation expected due to individual factors.

Our main population density research findings were that low-density tracts had statistically significantly higher built environment ratings than high density tracts, after controlling for individual demographic variables. When stratifying the models by population density, we found significantly less variation in perception in low-density tracts for all built environment scales. These findings did not entirely match our original hypotheses, as we expected to find more variation in aesthetic quality and safety in low density tracts, more variation in walking environment in medium density tracts, and no real pattern related to healthy food access.

In the median income analysis, we found the lowest mean scale scores (for all scales) in low median income tracts after controlling for demographic variables. After stratification, we found the most variation in perception in the lowest income tracts. These findings supported our initial hypotheses that variation in aesthetic quality and safety would drop as median income rose. The results did not support our hypothesis that middle-income areas would have more variation in walking environment or our hypothesis that there would be no variation for healthy food access.

The difference between many of our hypotheses and the findings, especially for the population density analysis, could be because population density does not capture the aspects of environmental context that we assumed it would. Other more complex measures of urban development may work better. Since we did have findings related to population density, however, it may also be that our assumption about variability in low-density areas was simply wrong. A subsequent analysis (not reported in a table) suggested a strong inverse relationship between population density and median income at the tract level, so our hypothesis that that variation would drop as both density and income rose was unlikely to hold.

Our models also produced some surprising results related to the main effects of some of the individual demographic variables. Though black non-Hispanics had lower mean scores for each scale (Table 4.3), after controlling for other demographic variables, the models found higher mean scores for three of the four scales (all but healthy food access) for black non-Hispanics as compared to white non-Hispanics. In some cases, we also saw unexpected associations between education and mean scale scores, though fewer of these were statistically significant. Because distribution of race/ethnic groups was associated with study site, we also ran the demographic-only model while controlling for site and still found the same association between race/ethnicity and education and mean scale scores.

We believe that the findings, despite not entirely supporting our initial hypotheses, are robust enough to warrant further examination in other settings and with other contextual variables. Though we do not presently have an explanation for all of our unexpected results, it is important to note that our hypothesis of greater variation in lower income areas was reflected in the results. Since other research has also determined that lower income areas are more likely to have lower access to health-promoting resources,[32-

[35] our findings could have implications for resource interventions in these areas. If residents of lower income areas demonstrate a wide range of perceptions of that environment, additional care may need to be taken to address resource gaps in a context of a wide range of perceptions.

We would like to offer two brief caveats to the interpretation of the questions posed in this analysis and its findings. First, the phenomenon of differing variation in perception is only tangentially related to the larger methodological debate surrounding the use of perceived or objective built environment data. Numerous studies have compared perceived and objective measures of the same constructs and found low levels of agreement.[36-39] Having posed some methodological questions about differences in variation, and having shown some of these differences across different environmental contexts, we do not think the "solution" to this issue is rely solely on objective data from third parties. Resident surveys will remain an important data gathering technique in this field and we have every reason to believe that individual perceptions are inextricably linked to behavior. Instead of shying away from perceived data, we think that variation in perception can actually be useful in forming clearer pictures of environments and how people interact with them.

Second, it should be noted that this analysis does not address the long-debated discussion surrounding the definition of a "neighborhood." The analysis occurs at the census tract level, despite the fact that the drawbacks of census tracts and other governmental geographic units are well understood.[40] Because census tracts remain a convenient unit of analysis, we think they will continue to be used in this field and it is important for research to be as analytically rigorous as possible. And even if the perfect neighborhood definition could be developed, it is possible that different neighborhoods could still elicit a range of perceptions from their residents. This research assumes that whatever the ideal neighborhood definition might be, aggregating measures to a larger unit of geography could introduce some measurement error, no matter what unit that is.

There are several limitations to this analysis. The main limitation is our inability to discern whether the context/variation relationship is due to something about the environmental context or whether it is due to real heterogeneity of the environment within census tracts. As suggested in the introduction, variation in perception could be due to individual characteristics, which were controlled for, or contextual characteristics, which were explored, or actual heterogeneity of the environment. At this time, with these data, it is impossible to quantify environmental heterogeneity, but the possibility that our environmental measures work "better" in some census tracts as compared to others is worth exploring, regardless of whether the cause of the problem is contextual or due to the geographic unit.

Other limitations include that the data set we used was limited to two major metropolitan areas. Future analyses should be expanded to other cities and more rural areas. The analysis also relies on two contextual variables, population density and median income, that were chosen because they offered a simple and straightforward way to illustrate the phenomenon. Given the mixture of expected and unexpected results, and the possibility that the crudeness of the population density measure contributed to the mixture, future analyses like this could benefit from examining variation based on more rigorous contextual measures of area socioeconomic status or urban design. In theory, it may be of interest to investigate the extent to which newer "walkable" communities, which include many characteristics thought to encourage active living, are not uniformly perceived that way.

Another limitation pertains to our test of statistical significance of the differences in fit between the pooled and stratified models. By adding interaction terms to the pooled model, we sought to make the fixed parts of the models uniform. Therefore, the likelihood ratio test should be testing whether model fit is improved by allowing variance components to differ across strata. However, other recent work done with different research questions have suggested that a bootstrap method may be more appropriate. Future analyses and software may us to employ this more elegant solution.

This analysis found that contextual variables impact not only perceptions of the environment, but also are associated with variation in those perceptions. We concluded that typical measures of the built environment may act differently in areas with different population densities or median income. In large studies that include a range of contexts, aggregation of individual perceptions could potentially mask important nuances of the built environment and people’s interaction with it. Since some research has suggested that changes in perception are linked with changes in behavior,[41] further elucidation of factors associated with differences in perception is needed, especially for different built environment constructs across a range of environmental contexts. As we move toward translating built environment research into built environment policies, the possibility of differential perception of both existing environments and policy-based changes to those environments, and subsequent possible differences in behaviors resulting from the changes, should be kept in mind.

Table 4.1: Built environment survey items and scale statistics

Aesthetic Quality	n=3775 / Chronbach's Alpha = 0.75
1. There is a lot of trash and litter on the street in my neighborhood[a] 2. There is a lot of noise in my neighborhood[a] 3. In my neighborhood the buildings and homes are well maintained[b] 4. The buildings and houses in my neighborhood are interesting[b] 5. My neighborhood is attractive[b]	
Healthy Food Access	n=3709 / Chronbach's Alpha = 0.78
1. A large selection of fresh fruits and vegetables is available in my neighborhood. [b] 2. The fresh fruits and vegetables in my neighborhood are of high quality[b] 3. A large selection of low fat foods is available in my neighborhood[b]	
Safety	n=3754 / Chronbach's Alpha = 0.75
1. I feel safe walking in my neighborhood day or night[b] 2. Violence is not a problem in my neighborhood[a] 3. My neighborhood is safe from crime.[b]	
Walking Environment	n=3668 / Chronbach's Alpha = 0.75
1. My neighborhood offers many opportunities to be physically active[b] 2. Local sports clubs & other facilities in my neighborhood offer many opportunities to get exercise[b] 3. It is pleasant to walk in my neighborhood[b] 4. The trees in my neighborhood provide enough shade[b] 5. In my neighborhood it is easy to walk places[b] 6. I often see other people walking in my neighborhood[b] 7. I often see other people exercising in my neighborhood, ie jogging, bicycling, or playing sports[b]	

All items were answered on a 5-point Likert scale from strongly disagree to strongly agree. For inclusion in the scale, items marked with an "a" were coded as 1=Strongly agree to 5=Strongly disagree and items marked with a "b" were reverse coded to 1=Strongly disagree to 5=Strongly agree.

Table 4.2: Descriptive statistics of the relationship between demographic variables and population density

	Total n=3883	Population Density			
		Low n=1274	Middle n=1217	High n=1392	p-value[a]
Female (%)	62.1	59.8	62.8	63.7	0.11
Median age (yrs)	50.0	54.0	48.0	48.0	<.001
Median time in neighborhood (yrs)	13.0	15.0	12.0	12.5	<.001
Race/ethnicity (%)					<.001
White non-Hispanic	36.4	45.9	32.9	30.9	
Black non-Hispanic	20.3	18.6	14.9	26.5	
Hispanic	35.0	21.8	45.6	37.9	
Asian	5.8	10.8	4.4	2.4	
Other	2.5	2.8	2.3	2.3	
Education (%)					<.001
High school or less	29.8	18.7	34.5	35.7	
Some college	26.4	28.9	28.0	22.6	
Bachelor or more	43.9	52.4	37.5	41.7	
Household income(%)					<.001
<$12,000	17.3	8.3	18.1	24.8	
$12-25,000	14.6	9.1	17.6	17.0	
$25-40,000	25.2	23.3	27.3	25.1	
$40-75,000	14.7	17.4	14.0	12.6	
>$75,000	28.2	41.8	23.1	20.4	
Site (%)					<.001
Los Angeles	48.3	80.9	62.9	5.8	
New York City	51.7	19.2	37.1	94.2	

[a] The p-value reflects the statistical significance of the association based on a chi-square test for the categorical variables (race, education, income, sex) and ANOVA for continuous variables (age, time in neighborhood).

Table 4.3: Descriptive statistics of the relationship between demographic variables and median income

	Median Income			
	Low n=1298	Middle n=1243	High n=1342	p-value[a]
Female (%)	64.9	60.0	61.5	0.03
Median age (yrs)	48.0	48.0	54.0	<0.001
Median time in neighborhood (yrs)	10.0	12.0	18.0	<0.001
Race/ethnicity (%)				<0.001
White non-Hispanic	13.0	28.7	66.2	
Black non-Hispanic	41.3	12.3	7.3	
Hispanic	39.8	49.6	16.9	
Asian	2.9	6.8	7.7	
Other	3.1	2.5	1.9	
Education (%)				<0.001
High school or less	42.1	35.2	12.7	
Some college	27.7	29.7	21.9	
Bachelor or more	30.1	35.1	65.4	
Household income(%)				<0.001
<$12,000	29.9	18.3	4.1	
$12-25,000	19.0	17.7	7.5	
$25-40,000	27.2	29.0	19.8	
$40-75,000	11.0	15.8	17.1	
>$75,000	12.9	19.2	51.5	
Site (%)				<0.001
Los Angeles	22.1	68.1	55.3	
New York City	77.9	31.9	44.7	

[a] The p-value reflects the statistical significance of the association based on a chi-square test for the categorical variables (race, education, income, sex) and ANOVA for continuous variables (age, time in neighborhood).

Table 4.4: Mean built environment scale response scores (1="worse" neighborhood to 5="better" neighborhood) by demographic characteristics and contextual factors

	Aesthetic Quality	p-value[a]	Healthy Food	p-value[a]	Safety	p-value[a]	Walking Environment	p-value[a]
Total Sample	3.48		3.45		3.34		3.70	
Sex		0.07		0.11		<0.001		0.07
Women	3.46		3.42		3.28		3.69	
Men	3.51		3.48		3.44		3.72	
Age[b]	0.24	<0.001	0.16	<0.001	0.13	<0.001	0.10	<0.001
Time in neighborhood[b]	0.13	<0.001	0.10	<0.001	0.07	<0.001	0.08	<0.001
Race/ethnicity		<0.001		<0.001		<0.001		<0.001
White non-Hispanic	3.67		3.70		3.66		3.90	
Black non-Hispanic	3.38		3.14		3.05		3.60	
Hispanic	3.30		3.34		3.11		3.54	
Asian	3.64		3.62		3.71		3.73	
Other	3.56		3.44		3.34		3.77	
Education		<0.001		<0.001		<0.001		<0.001
High school or less	3.35		3.38		3.08		3.54	
Some college	3.44		3.35		3.21		3.64	
Bachelor or more	3.59		3.55		3.59		3.84	
Household income		<0.001		<0.001		<0.001		<0.001
<$12,000	3.23		3.33		3.00		3.47	
$12-25,000	3.36		3.38		3.11		3.55	
$25-40,000	3.43		3.36		3.21		3.63	
$40-75,000	3.52		3.44		3.42		3.74	
>$75,000	3.72		3.63		3.72		3.95	
Site		<0.001		<0.001		<0.001		0.05
Los Angeles	3.68		3.51		3.46		3.68	
New York City	3.29		3.38		3.23		3.72	
Population Density		<0.001		<0.001		<0.001		<0.001
Low	3.91		3.63		3.75		3.88	
Medium	3.41		3.47		3.26		3.63	
High	3.20		3.33		3.17		3.71	
Median Income		<0.001		<0.001		<0.001		<0.001
Low	3.10		3.10		2.88		3.46	
Medium	3.40		3.34		3.21		3.58	
High	3.92		3.89		3.90		4.05	

[a] p-value for test of difference in means or correlation (for age and time in neighborhood only)
[b] Age and neighborhood tenure are continuous variables, so Pearson's correlation coefficients assessing their correlation with built environment scales are shown.

Table 4.5: Difference in mean scale scores associated with the main effects of demographic variables and contextual variables

	Aesthetic quality	Healthy food access	Safety	Walking environment
Race/ethnicity[a]				
White non-Hispanic	Ref	Ref	Ref	Ref
Black non-Hispanic	**0.18	-0.07	*0.09	*0.10
Hispanic	*0.10	0.04	0.03	0.02
Asian	0.08	0.13	0.10	-0.04
Other	*0.21	0.11	0.07	*0.14
Education[a]				
High school or less	Ref	Ref	Ref	Ref
Some college	*-0.06	*-0.10	-0.04	-0.02
Bachelor or more	-0.06	*-0.11	0.05	-0.02
Household income[a]				
<$12,000	Ref	Ref	Ref	Ref
$12-25,000	0.03	-0.01	-0.01	0.04
$25-40,000	0.03	-0.05	0.00	0.05
$40-75,000	0.05	-0.04	0.04	*0.07
>$75,000	*0.12	-0.04	*0.14	**0.16
Sex (female=ref)[a]	0.01	0.04	**0.12	0.02
Age (yrs)[a]	**0.01	**0.01	**0.003	0.00
Time in neighborhood (yrs)[a]	0.00	0.00	0.00	*0.002
Low population density	**0.77	**0.35	**0.68	**0.25
Medium population density	**0.30	*0.21	*0.23	0.06
High population density	Ref	Ref	Ref	Ref
Low median income	**-0.88	**-0.80	**-1.01	**-0.58
Medium median income	**-0.53	**-0.58	**-0.67	**-0.45
High median income	Ref	Ref	Ref	Ref

[a] The differences in mean scale scores for the individual demographic variables come from the demographic variable only model (which does not control for either contextual variable).
[b] The differences in mean scale scores for the contextual variables are reported from the main effects models that control for individual characteristics but do not include any interaction terms.

** < .001
*<.05

Table 4.6: Variance of perception of four built environment survey scales by population density from multi-level models controlling for individual demographic characteristics[a]

		Demographic variable-only model	Pop density main effect model	Low pop density stratum	Mid pop density stratum	High pop density stratum	p-value[b]
Aesthetic quality	Individual	0.89	0.89	0.66	0.95	1.05	
	Within Tract	0.21	0.21	0.17	0.24	0.22	
	Between Tract	0.19	0.09	0.12	0.07	0.09	
	ICC[c]	0.48	0.30	0.42	0.21	0.28	<0.01
Healthy food access	Individual	0.66	0.66	0.57	0.65	0.76	
	Within Tract	0.50	0.50	0.48	0.52	0.50	
	Between Tract	0.18	0.17	0.19	0.14	0.17	
	ICC	0.27	0.25	0.28	0.22	0.26	<0.01
Safety	Individual	0.74	0.74	0.59	0.74	0.87	
	Within Tract	0.35	0.35	0.31	0.41	0.32	
	Between Tract	0.26	0.17	0.24	0.18	0.12	
	ICC	0.43	0.33	0.43	0.30	0.27	<0.01
Walking environment	Individual	0.89	0.89	0.79	0.88	0.99	
	Within Tract	0.19	0.18	0.17	0.25	0.15	
	Between Tract	0.11	0.10	0.12	0.11	0.08	
	ICC	0.37	0.35	0.42	0.30	0.34	<0.01

[a] All models control for individual age, sex, race, education, income, and time spent in the neighborhood.

[b] The p-value refers to a likelihood ratio test comparing the main effect model, with interaction terms for all combinations of demographic and contextual variables, to the stratified model. The p-value determines whether to reject the hypothesis that model fit is not improved by allowing the variance parameters to vary by contextual strata.

[c] ICCs were calculated as between-tract variance divided by the sum of between- and within-tract variance and interpreted as the proportion of total variance that lies between the tracts

Table 4.7: Variance of perception of four built environment survey scales by median income from multi-level models controlling for individual demographic characteristics[a]

		Demographic variable-only model	Med income main effect model	Low med income stratum	Mid med income stratum	High med income stratum	p-value[b]
Aesthetic quality	Individual	0.89	0.89	1.04	0.87	0.76	
	Within Tract	0.21	0.21	0.27	0.23	0.13	
	Between Tract	0.19	0.08	0.03	0.11	0.09	
	ICC[c]	0.48	0.27	0.11	0.32	0.41	<0.01
Healthy food access	Individual	0.66	0.66	0.82	0.72	0.45	
	Within Tract	0.50	0.49	0.57	0.45	0.46	
	Between Tract	0.18	0.08	0.03	0.10	0.12	
	ICC	0.27	0.15	0.05	0.18	0.21	<0.01
Safety	Individual	0.74	0.74	0.96	0.73	0.54	
	Within Tract	0.35	0.35	0.37	0.41	0.26	
	Between Tract	0.26	0.10	0.04	0.14	0.13	
	ICC	0.43	0.23	0.09	0.26	0.33	<0.01
Walking environment	Individual	0.89	0.89	1.05	0.88	0.75	
	Within Tract	0.19	0.18	0.18	0.24	0.13	
	Between Tract	0.11	0.06	0.04	0.07	0.06	
	ICC	0.37	0.24	0.17	0.23	0.32	<0.01

[a] All models control for individual age, sex, race, education, income, and time spent in the neighborhood.

[b] The p-value refers to a likelihood ratio test comparing the main effect model, with interaction terms for all combinations of demographic and contextual variables, to the stratified model. The p-value determines whether to reject the hypothesis that model fit is not improved by allowing the variance parameters to vary by contextual strata.

[c] ICCs were calculated as between-tract variance divided by the sum of between- and within-tract variance and interpreted as the proportion of total variance that lies between the tracts

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Chapter 5

Conclusion

Human health is impacted by the environments in which we live, work, and play. Research that explores the complex relationship between these environments and health continues to expand. Due to some conflicting results and continued methodological concerns about the role of causality in built environment research, there are new calls for rigorous examination of measures and methodologies commonly used by researchers in this field.[1,2] This dissertation responds to those calls by examining how multiple, not just individual, health-related resources are patterned in environments, how the presence of multiple resources can be linked to clustering of healthy behaviors, and how a commonly-used technique could mask potentially important differences in environmental perceptions.

This concluding chapter begins with a restatement of the hypotheses that formed the foundation of each analysis, followed by a brief summary of findings from the dissertation relevant to each hypothesis. This chapter then concludes with an overall summary of how this dissertation contributes to built environment and health research, the limitations of the dissertation as a whole, and possible future research directions.

Demographic patterning of health-related resources (Chapter 2)

Hypothesis: Block groups with more non-whites will have poorer locational access to supermarkets and fresh food stores, recreational facilities, and retail areas. Block groups with more non-whites will have better locational access to park facilities.

Findings: We found evidence of a spatial association between individual and multiple resources and area race/ethnic composition. In Baltimore and Winston-Salem, spatial regression models showed that block groups with higher proportions of black residents tended to have lower supermarkets/produce, retail, and recreational facility densities, although these associations did not always achieve statistical significance. The regression analysis also showed that densities of supermarkets/produce stores, retail areas, and recreational facility activities were associated with area race/ethnicity, although the strength and significance of these associations varied by site.

Because park activity densities were not correlated with the other resources, and the main goal of the analysis was to examine race/ethnic predictors of resource clustering, we did not formally test the second part of the hypothesis above. Since block-groups with more non-whites were found to have diminished access to other resources, and these resources were negatively correlated with parks, it is likely that park access is higher in block groups with more non-whites.

Overall, these results are consistent with other work investigating associations of race/ethnic composition with each of the resources individually.[3-11] To the extent that health-related resources are associated with health and healthy behaviors, these findings suggest that the locations of a range of types of resources have the potential to contribute to or exacerbate race/ethnic health inequalities.

Hypothesis: Resources are clustered, such that block groups with low densities of a single resource are more likely to have low densities of all other resources, except parks. Block groups with more non-whites will have poorer access to clusters of health-related resources.

Findings: Three of the four block group-level resource densities (supermarkets/produce stores, retail areas, and recreational facilities) tended to be correlated with each other, whereas park activity density was less consistently and sometimes negatively correlated with the others. This suggests a clustering of non-park health-related resources at the block group level.

In each site there was evidence that block group race/ethnic composition was more strongly associated with a summary score of Health Opportunities than any of the individual resource densities that made up the score. In both Baltimore and Winston-Salem, a greater percentage of black residents were consistently and significantly associated with a lower health opportunities score, even when individual resources were not. In addition, at all three sites, clear differences across areas emerged when disadvantage across multiple resources was considered. If multiple resources act synergistically to affect health, the clustering of multiple types of disadvantage in space could have important implications for health inequities, a possibility that was explored more fully in Chapter 3.

Links between resources and healthy behaviors (Chapter 3)

Hypothesis: People who live in areas with higher Health Opportunities Scores will be more likely to report multiple healthy behaviors, as compared to people who live in areas with lower scores.

Findings: This analysis found that living in an area with a high Health Opportunities Score was associated with higher odds of exhibiting healthy behaviors including diet, physical activity, and walking. This finding supports existing literature linking environment and behavior, adds to the literature by showing an association between clustering of resources and clustering of behaviors, and also provides evidence that the Health Opportunities Score captures a meaningful health-related aspect of the environment.

Hypothesis: The Health Opportunities Score will demonstrate a synergistic association with healthy behaviors, such that the association will be above the level expected if the three components of the Health Opportunities Score were independently considered in a model.

Findings: We found evidence that the association between the Health Opportunities Score and healthy behaviors is synergistic, as residence near multiple health-related resources was associated with healthy behaviors above and beyond the association with individual resources. This finding, if replicated in future studies, could at least partially explain persistent health disparities, since it suggests that residents of resource-poor areas are at an even greater resource-related disadvantage than originally expected. The finding could also have wide-ranging implications for the type and location of built environment interventions. Whereas areas with an incomplete mix of resources could be greatly helped by the addition of one or two missing resources, areas with no resources might be addressed with a comprehensive plan.

Examination of built environment measures (Chapter 4)

Hypothesis: Individual demographic characteristics will be associated with perception of the built environment, but these associations will not account for all of the variation in perception seen within tracts.

Findings: We found evidence that supports this hypothesis. Nearly all demographic variables (sex, age, time in neighborhood, race/ethnicity, education, and household income) were associated with differences in mean built environment scale scores. After controlling for all of these variables in the regression models, there was still evidence of systematic within-unit differences in perception of the built environment.

Hypothesis: As population density and median income increase, variation in perceived aesthetic quality and perceived safety will decrease, because dense and wealthy tracts are likely to be less variable in aesthetic and safety features.

Findings: We found evidence to support the median income portion of this hypothesis. Within-tract variation in perception of aesthetic quality and safety diminished as median income rose. The population density models demonstrated the opposite relationship, as low density tracts had the least amount of variation in aesthetic quality and safety perception.

Hypothesis: There will be less variation in walking environments in high and low density and income tracts, because these tracts are likely to contain uniformly positive or poor walking environments.

Findings: We did not find evidence to support this hypothesis. In the population density analysis, the low density tracts had the lowest variation. In the median income analysis, the low income tracts had the most variation.

Hypothesis: Perception of healthy food access will not vary by population density or median income.

Findings: We did not find evidence to support this hypothesis. In the population density analysis, the low density tracts had the lowest variation. In the median income analysis, the low income tracts had the most variation.

Based on the findings from Chapter 4, we concluded that there is evidence of persistent variation in people's perception of the built environment within census tracts. We are confident this variation is not entirely due to individual demographic factors, unless there is an additional factor that we could not control for. The main limitation to this analysis, however, is our inability to discern whether the association between environmental context and variation is due to something about the environmental context or whether it is due to actual heterogeneity of the environment within census tracts. For now, it is impossible to quantify environmental heterogeneity, but the possibility that our environmental measures work "better" in some census tracts as compared to others is worth exploring, regardless of whether the cause of the problem is contextual or due to the geographic unit.

Collectively, all of the analyses that make up this dissertation pose, and at least start to answer, some novel questions in the field of built environment research. As this field is moving toward rigorous examination of environmental measures, this dissertation makes a solid and timely contribution to the field. In short, we found that race/ethnicity is associated with the clustering of multiple health related resources, whereas most of the existing research in this area examines single resources.[3,5,9,12] We also found that clustering of resources is associated with clustering of health behaviors, which could have important implications for addressing persistent inequities in health and health behaviors. Most existing research on clustering of health behaviors focuses on behavior patterns, not possible contextual factors associated with behavior clusters.[13-17] We also found that contextual factors predict variation in perception of the built environment, a finding that, if replicated in other areas and with other variables, could impact a commonly employed method of averaging survey measures within geographic units.

There are several limitations to the dissertation as a whole. The limitations that are specific to each analysis were discussed in each chapter, but some collective limitations that deserve mentioning. First, all analyses presented here are secondary data analyses. Though there is no reason to believe that the data sets contain any biases related to research questions, and all hypotheses were developed prior to analyzing the data, it is still possible that future data, collected to answer these specific questions, could find different results. Additionally, though the respondents who provided data for many of these analyses were identified with population-based approaches, it is likely that the geographic coverage of the data may not represent the true variety of environments with which people interact on a daily basis across the nation. Future analyses may benefit from a larger geographic scale or selection based on location variety.

Additionally, all three analyses include some unanswered questions about how to analyze built environment data from sites that exhibity very different types of urban development. On the one hand, it could be argued that there is no particular reason for there to be city-based differences in how perceptions and environment, or behaviors and environment, are associated with each other. If this is true, pooled analyses like those found in Chapters 3 and 4 are accurate. But there could be an argument that people in a dense urban area like Manhattan have a fundamentally different relationship with their environment, and therefore site-specific analyses like the one found in Chapter 2 is a better methodology. This dissertation does not answer this question, though it is something I would like to pursue with future research.

I remain interested in the some of the smaller details of built environment health research. In addition to continuing to explore site-specific differences in some of the associations found in the dissertation research, I think there are numerous future avenues for research in this field. Chapters 2 and 3 really just scratch the surface of creating an index of health opportunities, which could include many additional resources like sidewalks or bike lanes, and linking it to a selection of healthy behaviors, which could be expanded to include both behaviors and diseases. Chapter 4 only begins to illustrate how characteristics of environments are associated with a range of perceptions. This analysis could be extended to different contextual characteristics and additional areas.

In a more general sense, I plan to continue to find successful ways to pose research questions that combine the fields of public health and urban planning. In a world that is currently struggling with the simultaneous impacts of volatile oil prices, aging urban infrastructure, and declining local tax revenues, there will be continued efforts to re-think how we design our built environments to maximize their environmental and economic sustainability. A successful reunification of planning and public health will ensure that maximizing the health of the people living, working and playing in these environments is seen as an equally important goal in the policy decisions. Policy-making is not about deciding between people or places, but instead about recognizing how people and places interact in complex ways to produce a myriad of results. The interrelated challenges of disparities in urban investment and disparities in health outcomes offer an unfortunate, but potentially useful, place to start. And while research in this area is voluminous, there is still a need for critical examinations of specific issues that will eventually lead to solid policy recommendations.[18]

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